**Impact of Copyright Sharing on the Success of Non-Fungible Token Collections**

**Abstract**

The decision to share the copyright of NFT-associated artworks has sparked considerable debate. Copyright sharing benefits NFT collections by fostering broader participation 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 significantly increases the use of NFTs as social media profile pictures and positively affects average sale prices, 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.

*Keywords:* copyright sharing; network effects; non-fungible token; tokenization; remixing

1. **Introduction**

Non-fungible tokens (NFTs) are unique digital assets recorded on blockchains, which enables 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 on 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. By contrast, NFTs have unlocked liquidity and community participation of 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]](#footnote-1).

The copyright sharing approach, in which copyright owners voluntarily waive copyrights and dedicate 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 allows anyone to reuse, redistribute, and remix (build upon) the original artworks freely. This openness significantly increases the artworks’ visibility and dissemination across various platforms and communities, creating potential network effects and attracting a broader audience of buyers and creators. However, copyright sharing can also disincentivize creators by eliminating their ability to monetize their artworks via controlled licensing—such as royalties from commercial usage or advertising partnerships. Therefore, copyright sharing can enhance openness, liquidity, and network-driven growth but also may diminish creators’ economic incentives to contribute more to the NFT community.

Existing research on NFT success mainly focuses on the financial perspective, largely overlooking critical social dimensions. Specifically, prior studies have primarily concentrated 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 media platforms. By integrating analyses of both 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?*

Moreover, adopting copyright-sharing frameworks enables the broader community to engage in unrestricted remixing and derivative activities. Remixing is defined as the creative modification and recombination of original artworks into derivative works. We posit that remixing can cultivate a shared sense of inclusion, connection, and creative empowerment among community members. This, in turn, increases the likelihood that individuals will adopt the associated NFT images as their profile pictures, actively signaling membership and identity within NFT communities. Moreover, remixing contributes to financial success by acting as a catalyst for the rapid dissemination of cultural symbols. The widespread creation and circulation of derivative works can generate heightened public awareness, attract new buyers, and spur cultural innovation [7, 8]. Consequently, these factors enhance NFT collections’ overall desirability and perceived value, ultimately driving higher market prices through increased demand. As remixing amplifies network effects by increasing social visibility and market engagement, NFT collections that are more likely to be remixed can potentially achieve greater social influence and financial returns. This 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 empirically examine the impact of copyright sharing on NFT success and the role of remixing by analyzing panel data from 4,186 NFT collections over 81 weeks, spanning from the 31st week of 2021 to the 7th week of 2023. The data is 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 provides several contributions. First, by empirically examining the impacts of copyright sharing in NFT ecosystems, we expand both the NFT and intellectual property (IP) sharing literature. Previous studies on IP rights sharing for digital resources [8-11] 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 not merely financial assets but also 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 serves as a crucial moderating factor, which significantly enhances 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 critically depends on fostering and sustaining active remixing behaviors among community participants.

The remainder of this paper is structured as follows. In Section 2, we review relevant literature and develop hypotheses supported by the theory of network effects and various literature. 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.

1. **Literature Review and Hypothesis Development**

Figure 1 presents the research framework of our study. The first hypothesis (H1) examines the impact of copyright sharing on the success of NFT collections, considering both social and financial perspectives. From a social standpoint, the 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 [12-20]. The higher the proportion of NFTs used as profile pictures within a collection, the more broadly recognized and socially valuable the collection is perceived. Additionally, price is used as the metric to indicate financial success. The second hypothesis (H2) explores the moderating role of the propensity for remixing in the relationships examined in H1. The subsequent discussion in this section develops hypotheses by reviewing relevant literature and using the theory of network effects.

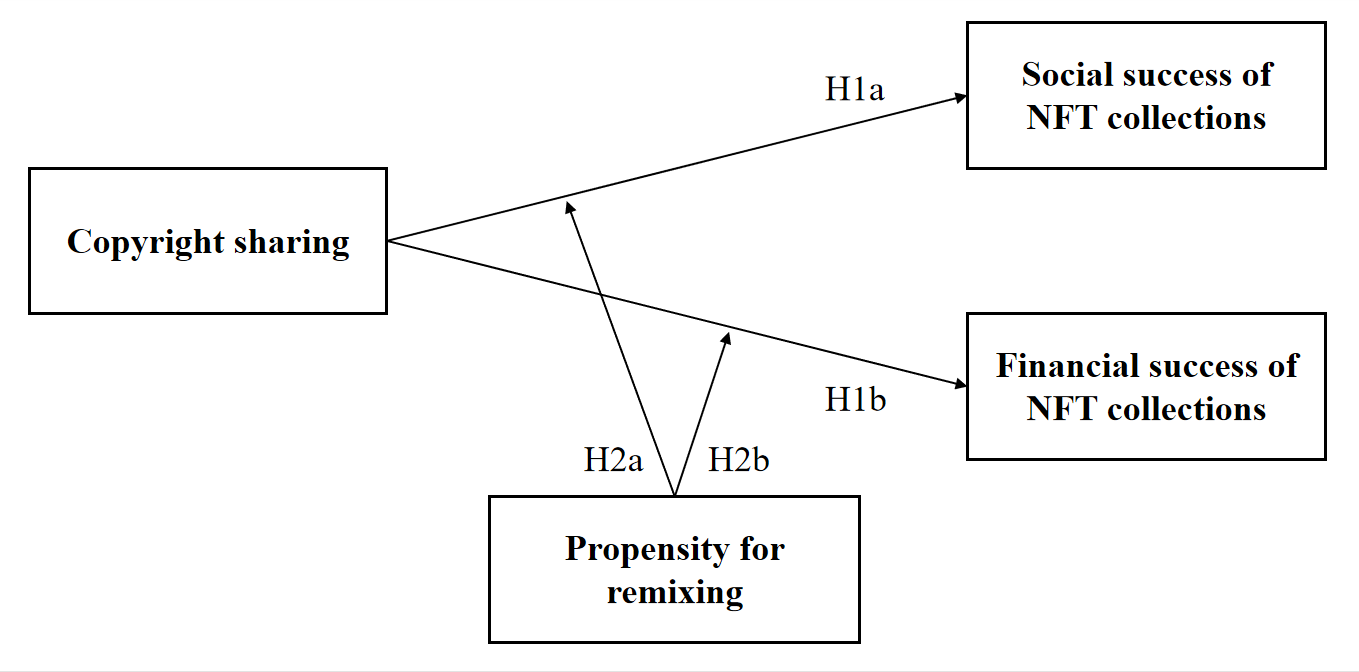


Figure 1. Research framework

* 1. *The Impact of Copyright Sharing on the Success of NFTs*

Network effects play a crucial role in determining the success of NFT collections since the development of NFT collections is collaborative. NFT creators usually rely not only on their internal capabilities but also on the active participation of a broader community. As more individuals engage with the ecosystem—whether through buying, creating, or promoting—the overall development of the NFT collection is amplified. The theory of network effects (or network externalities) describes the phenomenon in which the utility of participants or the value of a product increases as more people use it [21, 22]. These effects can be direct, where participants benefit from direct interaction with others, or indirect, where the benefits arise from the availability of complementary goods or services [23-25]. In the case of NFTs, network effects are crucial. Network effects are widely discussed in other contexts like software [26-29], entertainment [30-32], and other digital platforms [33, 34].

Copyright sharing enhances the ability to generate network effects, thereby contributing to greater social success, particularly in using NFTs from specific collections as profile pictures on social media. By giving up exclusive copyright control, the barriers to entry for new contributors are lowered, allowing a wider range of individuals to create derivative works, such as memes and remixes [35-38]. This increases the diffusion of the original NFT collection, attracting additional participants, and then a positive feedback loop is established [31, 34]. The growing involvement within the community strengthens a collective identity, making the NFTs more desirable as symbols of affiliation [39]. Consequently, users are more likely to adopt NFTs from these collections as profile pictures to signal their membership in the community. 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.*

Copyright sharing can also lead to greater financial success by strengthening network effects. For NFT collections, the choice between a closed or open copyright model significantly influences their potential to stimulate network effects [40]. Previous literature has recognized the network effect as a critical source of business value [33, 41-43]. By enabling users to interact with the content freely, copyright sharing encourages the creation of complementary works, such as derivative NFT collections, memes on social media, physical merchandise, and other creative transformations. As the number of these complementary creations increases, the functionality and cultural richness of the NFT collection expand, enhancing the utility of owning NFTs from the collection [44, 45]. This, in turn, increases the demand for the NFTs, ultimately driving up the price of the collection.

Despite the advantages of copyright sharing, several drawbacks have been discussed in previous studies. NFT creators and owners may not profit exclusively from their intellectual property if they share it freely [46]. Copyright sharing can also lead to a loss of control [47], increasing the risk of malicious use [48] and the emergence of copycats [9, 49]. 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 (i.e., tokenization) and the industry environment of NFTs (i.e., 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 permission lessness are widely accepted as social norms [50, 51]. 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 [52]. 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 overcomes the above drawbacks and drives the financial success of NFT collections:

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

* 1. *The Role of Remixing*

Remixing (i.e., reworking and recombining existing creative elements) is an essential form of community engagement [53, 54]. Community members reuse, alter, and build upon the foundational artwork of NFTs, thereby facilitating the creation of memes and the generation of novel ideas [8]. 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’ own interests and interpretations [53, 55]. Scholars have also adopted remixing to characterize the processes of knowledge reuse and recombination [8, 10, 56, 57].

Copyright sharing encourages community members to engage in remixing. However, the extent to which remixing occurs varies across NFT collections due to differences in the artworks associated with each collection. We hypothesize that the positive impact of copyright sharing on NFT success will be more pronounced when the images in the collection are more likely to be remixed. This assumption is grounded in the theory of network effects, where remixing acts as a form of community engagement and complementary creation that contributes to the success of the NFT collection.

There are three key reasons why remixing—an essential trigger for network effects—is crucial for the social success of an NFT collection: First, accessing a collection’s vital resources and innovating with them signifies that community members have integrated into the collection’s core, perceiving themselves as culture producers rather than mere recipients [58, 59]. This sense of inclusion fosters a stronger inclination to signal group membership. Second, the opportunity for members to collaborate and share knowledge during the remixing process strengthens interpersonal connections. Strengthened connections are another reason people identify as one group and use the NFT images to show their membership [60]. Finally, empowering community members to utilize the artwork and participate in decision-making processes freely reduces their uncertainty regarding the collection’s future [61]. This reduction in uncertainty is critical, as it is a proven motivator for identity formation [59, 62]. Therefore, the impact of copyright sharing on social success varies across NFT collections, being more pronounced where there is a greater propensity for remixing. We propose the following 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.*

Similarly, the likelihood of remixing is a critical condition for financial success under the framework of network effects. Firstly, as individuals remix and share their creations on social media, the visibility of the NFT collection increases exponentially. This broadcasting of derivative works enhances the collection’s reach and facilitates its memetic diffusion, where each remix acts as a unique interpretation that spreads the collection’s cultural appeal [7, 11, 55, 63]. As the collection becomes more visible and culturally resonant, it attracts more potential buyers, thereby increasing its market value.

Secondly, remixing not only increases the collection’s diffusion but also enables its evolution [8]. Community members with diverse backgrounds build upon the original NFTs to generate complementary works, akin to assembling modular components (e.g., LEGO pieces) that enrich the ecosystem [60, 64]. This process enhances the intrinsic value of the NFT collection, which, in turn, drives up its sale price. Therefore, the more likely an image is to be remixed, the more dynamic and evolving the ecosystem becomes, increasing its financial value:

*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.*

1. **Data, Measurements, and Regression Models**
   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 4,186 Ethereum ERC721[[2]](#footnote-2) NFT collections from NFTGO, a leading data analysis platform for NFTs. Based on the listing requirements of NFTGO[[3]](#footnote-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 their official X accounts via the X API. We also collect data on the use of NFTs as profile pictures on X from the Inspect website, as well as 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 covers 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 extend from October 2022 onwards due to limitations in data availability[[4]](#footnote-4).

* 1. *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 [65, 66]. 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 Figure 2).



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

* + 1. *Measuring the propensity for 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 for individuals to generate derivative works. This can be attributed to the fact that highly complex visual works are often too intricate to easily understand or use, potentially deterring creators [67, 68]. Moreover, complex works typically offer limited scope for re-creation, while simpler works provide more opportunities for innovation [53]. On the other hand, excessively simplistic 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 [53]. 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 [69, 70]. 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 [71].

The second widely used method for assessing image complexity is JPEG compression [71-74]. 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 (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 |  | The proportion of NFTs within a collection utilized as X profile pictures |
| Average sale price |  | The average sale price of NFTs in a collection |
| CC0 |  | 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 |  | The average mint price of NFTs in a collection |
| Supply |  | The cumulative number of NFTs minted for a collection (in thousands) |
| Transaction number |  | The transaction number of NFTs in a collection |
| Awareness |  | 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 |

* 1. *Regression Models*

To analyze the success differences between NFT collections that have adopted CC0 and those that have not[[5]](#footnote-5), we employ panel data using collection-week units (the collection is denoted by *i* and 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 important 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 Böckerman and Ilmakunnas [75], Heyman, Sjöholm and Tingvall [76], 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, the above matching procedure is conducted week-by-week (i.e., we implement matching 81 times). Finally, to check the validity of the matching, covariate balancing is tested. The results consistently show that, after matching, the differences in covariate means between CC0 and non-CC0 NFT collections are significantly reduced, with the difference no longer being significant (see Appendix A). The initial sample of 4,186 NFT collections is refined to 2,677 following the matching.

To test H1a and H1b, we use regression models that include NFT category dummies () and week dummies () to account for potential influences from NFT category characteristics and temporal trends. Additionally, we include NFT collection random effects (), which is supported by the Breusch-Pagan Lagrange Multiplier test (Prob > chi2 = 0.000). It is important to note that as our independent variable () 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 the level of public interest in a collection. More popular NFT collections are more likely to be used as profile pictures and to see higher demand, thereby increasing their sale price. Finally, we also control for the lagged sale price to account for the potential impact of past prices on current outcome variables. The coefficient is of our interest.

|  |  |  |
| --- | --- | --- |
|  |  |  |
| (1) |
|  |  |  |
|  |  |  |
| (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 Equations (1) and (2) to determine if reaches its highest value at a medium complexity level.

1. **Results and Additional Analysis**
   1. Descriptive Summary Statistics and Correlations

Table 2 provides descriptive summary statistics for 113,914 observations across NFT collections over time. 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 Equations (1) and (2), following the approach outlined by Chatterjee and Hadi [77]. 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.

Table 2. Descriptive summary statistics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Obs | Mean | Std. Dev. | Min | Max |
|  | 16,294 | 0.025 | 0.063 | 0.000 | 0.786 |
|  | 113,914 | 2.135 | 65.510 | 0.000 | 8572.040 |
|  | 113,914 | 0.039 | 0.194 | 0.000 | 1.000 |
|  | 105,568 | 245467.360 | 156340.670 | 12051.000 | 1132240.800 |
|  | 105,568 | 201080.740 | 107951.970 | 6237.000 | 792397.200 |
|  | 113,914 | 6.546 | 4.864 | 0.014 | 100.000 |
|  | 113,914 | 0.125 | 0.420 | 0.000 | 30.000 |
|  | 113,914 | 130.023 | 565.494 | 1.000 | 27409.000 |
|  | 113,914 | 1.663 | 14.209 | 0.000 | 1659.574 |

Table 3. Correlation matrix

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|  | 1.000 |
|  | 0.016 | 1.000 |
|  | -0.007 | -0.001 | 1.000 |
|  | -0.083 | -0.018 | -0.080 | 1.000 |
|  | -0.094 | -0.015 | -0.095 | 0.902 | 1.000 |
|  | 0.064 | 0.017 | -0.026 | -0.041 | -0.035 | 1.000 |
|  | 0.069 | 0.039 | -0.027 | 0.018 | 0.020 | -0.078 | 1.000 |
|  | 0.248 | -0.002 | -0.003 | -0.052 | -0.054 | 0.176 | 0.010 | 1.000 |
|  | 0.206 | 0.024 | -0.014 | -0.025 | -0.025 | 0.076 | -0.002 | 0.088 | 1.000 |
|  | | | | | | | | | |

* 1. *Main Regression Results*
     1. *The Impact of Copyright Sharing on the Social Success of NFT Collections*

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

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.009\*\*\* | -0.002 | 0.066\*\*\* | 0.002 |
|  | (0.003) | (0.009) | (0.003) | (0.003) |
|  | 0.001\*\*\* | 0.002\*\*\* | 0.000\*\*\* | 0.000\* |
|  | (0.000) | (0.001) | (0.000) | (0.000) |
|  | 0.001\*\* | 0.002\*\*\* | 0.001\*\*\* | 0.000 |
|  | (0.000) | (0.001) | (0.000) | (0.000) |
|  | 0.004\*\*\* | 0.004\* | 0.002 | 0.003\*\*\* |
|  | (0.001) | (0.002) | (0.001) | (0.001) |
|  | -0.000 | -0.000 | -0.000 | 0.000 |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.245 | 0.165 | 0.179 | 0.712 |
| Observations | 14,853 | 4,746 | 5,132 | 4,396 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.009\*\*\* | -0.002 | 0.057\*\*\* | 0.001 |
|  | (0.003) | (0.010) | (0.005) | (0.004) |
|  | 0.001\*\*\* | 0.002\*\*\* | 0.002\*\*\* | 0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 0.001\*\* | 0.002\* | 0.002\*\*\* | -0.000\* |
|  | (0.000) | (0.001) | (0.001) | (0.000) |
|  | 0.004\*\*\* | 0.005\*\* | 0.005\*\*\* | 0.002\*\*\* |
|  | (0.001) | (0.002) | (0.001) | (0.001) |
|  | -0.000 | -0.000\*\* | 0.000\*\*\* | -0.000 |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.245 | 0.096 | 0.264 | 0.887 |
| Observations | 14,853 | 5,048 | 4,911 | 4,315 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

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 grouped regression analysis shows that the coefficient for CC0 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 insignificant 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, images are more likely to be remixed by community members. This highlights the essential role of remixing in enhancing the effectiveness of copyright-sharing strategies, thereby supporting H2a.

* + 1. *The Impact of Copyright Sharing on the Financial Success of NFT Collections*

The result of Equation (2) is presented in column (1) of Tables 6 and 7, which indicates that NFT collections employing the CC0 license, a copyright-sharing strategy, experience an average increase of 12.8% () in their sale price compared to non-CC0 collections, with all other variables held constant. 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 insignificantly different from zero. While for NFT collections with a medium level of image complexity, the coefficient of CC0 is the highest and most significant. Specifically, a 14.4% () and a 12.3% () 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 mixed is higher than 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.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.121\*\*\* | 0.106 | 0.135\*\* | 0.069 |
|  | (0.023) | (0.104) | (0.058) | (0.058) |
|  | 0.563\*\*\* | 0.762\*\*\* | 0.618\*\*\* | 0.688\*\*\* |
|  | (0.016) | (0.018) | (0.020) | (0.042) |
|  | 0.001 | -0.002 | -0.003 | -0.000 |
|  | (0.003) | (0.003) | (0.002) | (0.003) |
|  | 0.151\*\*\* | 0.088\*\*\* | 0.137\*\*\* | 0.114\*\*\* |
|  | (0.008) | (0.010) | (0.019) | (0.018) |
|  | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.680 | 0.736 | 0.659 | 0.716 |
| Observations | 102,494 | 31,361 | 31,922 | 31,774 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.121\*\*\* | 0.094 | 0.117\*\*\* | 0.091 |
|  | (0.023) | (0.087) | (0.029) | (0.091) |
|  | 0.563\*\*\* | 0.720\*\*\* | 0.733\*\*\* | 0.738\*\*\* |
|  | (0.016) | (0.016) | (0.021) | (0.026) |
|  | 0.001 | -0.002 | -0.003 | -0.003 |
|  | (0.003) | (0.003) | (0.003) | (0.002) |
|  | 0.151\*\*\* | 0.107\*\*\* | 0.101\*\*\* | 0.094\*\*\* |
|  | (0.008) | (0.009) | (0.018) | (0.009) |
|  | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.680 | 0.726 | 0.716 | 0.677 |
| Observations | 102,494 | 31,359 | 31,938 | 31,760 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

* 1. *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, theme, or the nature of the digital asset they represent. A comprehensive list of NFT categories is provided in Table 1. Our data shows that CC0 adoption is most prevalent in four categories: profile picture, collectible, 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 like 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 like 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 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.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Profile pictures | Collectibles | Art | Metaverse |
|  | 0.012\*\* | 0.008\*\*\* | 0.010\*\*\* | -0.028 |
|  | (0.006) | (0.001) | (0.000) | (0.017) |
|  | 0.001\*\*\* | 0.000\*\*\* | 0.000\* | 0.006 |
|  | (0.000) | (0.000) | (0.000) | (0.004) |
|  | 0.001\* | 0.001\*\*\* | 0.000 | -0.002 |
|  | (0.001) | (0.000) | (0.000) | (0.003) |
|  | 0.005\*\* | 0.002\*\*\* | 0.004 | -0.008 |
|  | (0.002) | (0.000) | (0.003) | (0.011) |
|  | -0.000\*\* | 0.000\*\*\* | -0.000 | -0.000 |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.228 | 0.087 | 0.277 | 0.301 |
| Observations | 10,985 | 1,668 | 800 | 356 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Profile pictures | Collectibles | Art | Metaverse |
|  | 0.107\*\*\* | 0.174\*\*\* | 0.037\* | 0.499\* |
|  | (0.010) | (0.024) | (0.019) | (0.290) |
|  | 0.596\*\*\* | 0.645\*\*\* | 0.866\*\*\* | 0.715\*\*\* |
|  | (0.004) | (0.009) | (0.024) | (0.054) |
|  | -0.002\*\*\* | -0.000 | -0.003\*\* | 0.002 |
|  | (0.001) | (0.000) | (0.002) | (0.009) |
|  | 0.131\*\*\* | 0.132\*\*\* | 0.053\*\*\* | 0.157\* |
|  | (0.005) | (0.002) | (0.008) | (0.082) |
|  | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.669 | 0.658 | 0.747 | 0.690 |
| Observations | 62,794 | 16,021 | 7,148 | 3,584 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

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 predominantly relies on their artistic value, less influenced by licensing.

* 1. *Robustness Checks*
     1. *Changing Price Unit from ETH to USD*

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.008\*\*\* | -0.004 | 0.065\*\*\* | 0.002 |
|  | (0.003) | (0.008) | (0.002) | (0.002) |
|  | 0.001\*\*\* | 0.003\*\*\* | 0.000\*\*\* | 0.000 |
|  | (0.000) | (0.001) | (0.000) | (0.000) |
|  | 0.001\*\* | 0.002\*\*\* | 0.001\*\*\* | 0.000 |
|  | (0.000) | (0.001) | (0.000) | (0.000) |
|  | 0.004\*\*\* | 0.003\* | 0.002\* | 0.003\*\*\* |
|  | (0.001) | (0.002) | (0.001) | (0.001) |
|  | -0.000 | -0.000 | -0.000 | 0.000 |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.245 | 0.178 | 0.179 | 0.713 |
| Observations | 14,853 | 4,746 | 5,132 | 4,396 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

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 Equations (1) and (2). The findings presented in Tables 10 and 11 provide similar conclusions, thereby confirming the robustness of our results.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.064\*\*\* | 0.085 | 0.122\*\* | 0.063 |
|  | (0.022) | (0.090) | (0.057) | (0.062) |
|  | 0.589\*\*\* | 0.730\*\*\* | 0.629\*\*\* | 0.690\*\*\* |
|  | (0.016) | (0.023) | (0.024) | (0.035) |
|  | -0.002 | -0.005 | -0.006\*\* | -0.001 |
|  | (0.003) | (0.003) | (0.002) | (0.003) |
|  | 0.130\*\*\* | 0.095\*\*\* | 0.121\*\*\* | 0.097\*\*\* |
|  | (0.006) | (0.012) | (0.013) | (0.014) |
|  | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.768 | 0.812 | 0.746 | 0.819 |
| Observations | 102,275 | 31,279 | 31,888 | 31,765 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

* + 1. *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 individual 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 alter to the logarithm of the weekly volume traded. 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 conducting grouped regression analyses, 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 12. Impact of copyright sharing on financial success (volume traded): Grouped regression results based on Canny complexity

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.305\*\* | 0.310 | 0.474\*\* | 0.031 |
|  | (0.113) | (0.189) | (0.148) | (0.098) |
|  | 0.671\*\*\* | 0.729\*\*\* | 0.718\*\*\* | 0.704\*\*\* |
|  | (0.021) | (0.033) | (0.025) | (0.082) |
|  | 0.105\*\*\* | 0.133\*\*\* | 0.120\*\*\* | 0.086\*\*\* |
|  | (0.027) | (0.037) | (0.028) | (0.024) |
|  | 0.098\*\*\* | 0.101\*\*\* | 0.098\*\*\* | 0.054 |
|  | (0.019) | (0.019) | (0.029) | (0.038) |
|  | 0.002\*\*\* | 0.002\*\*\* | 0.001\*\*\* | 0.001\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | -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-squared | 0.587 | 0.640 | 0.596 | 0.594 |
| Observations | 102,494 | 31,361 | 31,922 | 31,774 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

* + 1. *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 them 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.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.009\*\*\* | -0.002 | 0.054\*\*\* | 0.004 |
|  | (0.003) | (0.010) | (0.004) | (0.003) |
|  | 0.001\*\*\* | 0.002\*\*\* | 0.000\*\*\* | 0.000\*\* |
|  | (0.000) | (0.001) | (0.000) | (0.000) |
|  | 0.001\*\* | 0.002\*\*\* | 0.001\*\*\* | 0.000 |
|  | (0.000) | (0.001) | (0.000) | (0.000) |
|  | 0.004\*\*\* | 0.004\* | 0.002 | 0.004\*\*\* |
|  | (0.001) | (0.002) | (0.001) | (0.001) |
|  | -0.000 | -0.000\* | 0.000\* | 0.000 |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.245 | 0.154 | 0.163 | 0.688 |
| Observations | 14,853 | 4,634 | 5,197 | 4,443 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.121\*\*\* | 0.099 | 0.138\*\* | 0.106\* |
|  | (0.023) | (0.089) | (0.070) | (0.057) |
|  | 0.563\*\*\* | 0.806\*\*\* | 0.593\*\*\* | 0.659\*\*\* |
|  | (0.016) | (0.015) | (0.023) | (0.042) |
|  | 0.001 | -0.002 | -0.001 | -0.002 |
|  | (0.003) | (0.002) | (0.003) | (0.004) |
|  | 0.151\*\*\* | 0.073\*\*\* | 0.147\*\*\* | 0.122\*\*\* |
|  | (0.008) | (0.008) | (0.018) | (0.020) |
|  | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.680 | 0.739 | 0.654 | 0.716 |
| Observations | 102,494 | 31,417 | 31,982 | 31,658 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.009\*\*\* | -0.006 | 0.026\*\*\* | 0.002 |
|  | (0.003) | (0.008) | (0.006) | (0.005) |
|  | 0.001\*\*\* | 0.000\*\*\* | 0.002\*\*\* | 0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 0.001\*\* | 0.001\*\*\* | 0.001\*\*\* | 0.000 |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 0.004\*\*\* | 0.001\* | 0.005\*\*\* | 0.005\*\*\* |
|  | (0.001) | (0.001) | (0.002) | (0.002) |
|  | -0.000 | -0.000\*\* | 0.000\*\*\* | 0.000 |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.245 | 0.144 | 0.170 | 0.434 |
| Observations | 14,853 | 4,253 | 5,382 | 4,639 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.121\*\*\* | 0.121\* | 0.159\*\* | -0.065 |
|  | (0.023) | (0.073) | (0.066) | (0.054) |
|  | 0.563\*\*\* | 0.789\*\*\* | 0.614\*\*\* | 0.595\*\*\* |
|  | (0.016) | (0.017) | (0.018) | (0.035) |
|  | 0.001 | -0.002 | 0.004 | -0.008 |
|  | (0.003) | (0.002) | (0.003) | (0.007) |
|  | 0.151\*\*\* | 0.077\*\*\* | 0.148\*\*\* | 0.137\*\*\* |
|  | (0.008) | (0.010) | (0.013) | (0.027) |
|  | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.680 | 0.708 | 0.716 | 0.673 |
| Observations | 102,494 | 31,700 | 31,683 | 31,674 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

* + 1. *Using Different Matching Methods*

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.008\*\*\* | -0.003 | 0.066\*\*\* | 0.002 |
|  | (0.003) | (0.008) | (0.002) | (0.003) |
|  | 0.001\*\*\* | 0.002\*\*\* | 0.000\*\*\* | 0.000\* |
|  | (0.000) | (0.001) | (0.000) | (0.000) |
|  | 0.001\*\* | 0.002\*\*\* | 0.001\*\*\* | 0.000 |
|  | (0.000) | (0.001) | (0.001) | (0.000) |
|  | 0.004\*\*\* | 0.004\* | 0.002\*\* | 0.003\*\*\* |
|  | (0.001) | (0.002) | (0.001) | (0.001) |
|  | -0.000 | -0.000 | -0.000\* | 0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.239 | 0.131 | 0.169 | 0.752 |
| Observations | 13,926 | 4,458 | 4,836 | 4,083 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Dependent variable: | | | |
|  | (1) | (2) | (3) | (4) |
|  | Full sample | Low complexity | Medium complexity | High complexity |
|  | 0.095\*\*\* | 0.076 | 0.105\* | 0.040 |
|  | (0.020) | (0.116) | (0.055) | (0.056) |
|  | 0.601\*\*\* | 0.710\*\*\* | 0.639\*\*\* | 0.772\*\*\* |
|  | (0.015) | (0.020) | (0.015) | (0.040) |
|  | -0.005\*\* | -0.007\* | -0.005 | -0.007\*\*\* |
|  | (0.002) | (0.004) | (0.004) | (0.003) |
|  | 0.125\*\*\* | 0.085\*\*\* | 0.118\*\*\* | 0.077\*\*\* |
|  | (0.004) | (0.010) | (0.016) | (0.012) |
|  | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* | 0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) |
|  | 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-squared | 0.675 | 0.721 | 0.649 | 0.707 |
| Observations | 95,501 | 29,343 | 29,707 | 29,463 |

\*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1. Standard errors in parentheses.

1. **Conclusion**

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 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, thereby 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 empirically 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 freely used 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 further contributes 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 behaviors such as herding, and price prediction. It has primarily 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.

At 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, primarily due to data availability issues. First, data on the adoption of NFTs as profile pictures on social media platforms is 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 covers 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.

1. **References**

[1] J. Branny, R. Dornberger, T. Hanne, Non-fungible token price prediction with multivariate LSTM neural networks, in: 2022 9th International Conference on Soft Computing & Machine Intelligence (ISCMI), IEEE, 2022, pp. 56-61.

[2] R. Hofstetter, M.P. Fritze, C. Lamberton, Beyond scarcity: A social value-based lens for NFT pricing, Journal of Consumer Research, 51 (2024) 140-150.

[3] F. Horky, C. Rachel, J. Fidrmuc, Price determinants of non-fungible tokens in the digital art market, Finance Research Letters, 48 (2022) 103007.

[4] A. Kapoor, D. Guhathakurta, M. Mathur, R. Yadav, M. Gupta, P. Kumaraguru, Tweetboost: Influence of social media on nft valuation, in: Companion Proceedings of the Web Conference 2022, 2022, pp. 621-629.

[5] M. Nadini, L. Alessandretti, F. Di Giacinto, M. Martino, L.M. Aiello, A. Baronchelli, Mapping the NFT revolution: market trends, trade networks, and visual features, Scientific reports, 11 (2021) 20902.

[6] V. Buterin, The most important scarce resource is legitimacy, in: Vitalik Buterin's Website, 2021.

[7] S. Bapna, M.J. Benner, L. Qiu, Nurturing online communities: An empirical investigation, MIS Quarterly, 43 (2019).

[8] Y. Han, P. Ozturk, J.V. Nickerson, Leveraging the wisdom of the crowd to address societal challenges: revisiting the knowledge reuse for innovation process through analytics, Journal of the Association for Information Systems, 21 (2020) 8.

[9] K. Karhu, R. Gustafsson, K. Lyytinen, Exploiting and defending open digital platforms with boundary resources: Android’s five platform forks, Information Systems Research, 29 (2018) 479-497.

[10] F. Murray, S. Stern, Do formal intellectual property rights hinder the free flow of scientific knowledge?: An empirical test of the anti-commons hypothesis, Journal of Economic Behavior & Organization, 63 (2007) 648-687.

[11] L. Zhang, Intellectual property strategy and the long tail: Evidence from the recorded music industry, Management Science, 64 (2018) 24-42.

[12] J. Berger, Word of mouth and interpersonal communication: A review and directions for future research, Journal of Consumer Psychology, 24 (2014) 586-607.

[13] J. Berger, C. Heath, Where consumers diverge from others: Identity signaling and product domains, Journal of Consumer Research, 34 (2007) 121-134.

[14] J. Berger, C. Heath, Who drives divergence? Identity signaling, outgroup dissimilarity, and the abandonment of cultural tastes, Journal of Personality and Social Psychology, 95 (2008) 593.

[15] C. Chan, J. Berger, L. Van Boven, Identifiable but not identical: Combining social identity and uniqueness motives in choice, Journal of Consumer Research, 39 (2012) 561-573.

[16] H. Geva, G. Oestreicher-Singer, M. Saar-Tsechansky, Using retweets when shaping our online persona: Topic modeling approach, MIS Quarterly, 43 (2019) 501-524.

[17] L. Grewal, A.T. Stephen, N.V. Coleman, When posting about products on social media backfires: The negative effects of consumer identity signaling on product interest, Journal of Marketing Research, 56 (2019) 197-210.

[18] J. Savary, R. Dhar, The uncertain self: How self-concept structure affects subscription choice, Journal of Consumer Research, 46 (2020) 887-903.

[19] Y. Wang, V. Griskevicius, Conspicuous consumption, relationships, and rivals: Women's luxury products as signals to other women, Journal of Consumer Research, 40 (2014) 834-854.

[20] X. Zeng, L. Wei, Social ties and user content generation: Evidence from Flickr, Information Systems Research, 24 (2013) 71-87.

[21] J.M. Gallaugher, Y.-M. Wang, Understanding network effects in software markets: Evidence from web server pricing, MIS Quarterly, (2002) 303-327.

[22] M.L. Katz, C. Shapiro, Network externalities, competition, and compatibility, The American Economic Review, 75 (1985) 424-440.

[23] D. Birke, The economics of networks: A survey of the empirical literature, Journal of Economic Surveys, 23 (2009) 762-793.

[24] H.K. Cheng, Y. Liu, Q. Tang, The impact of network externalities on the competition between open source and proprietary software, Journal of Management Information Systems, 27 (2011) 201-230.

[25] O. Shy, A short survey of network economics, Review of Industrial Organization, 38 (2011) 119-149.

[26] A. Bonaccorsi, S. Giannangeli, C. Rossi, Entry strategies under competing standards: Hybrid business models in the open source software industry, Management Science, 52 (2006) 1085-1098.

[27] H.K. Cheng, Y. Liu, Optimal software free trial strategy: The impact of network externalities and consumer uncertainty, Information Systems Research, 23 (2012) 488-504.

[28] N. Economides, E. Katsamakas, Two-sided competition of proprietary vs. open source technology platforms and the implications for the software industry, Management Science, 52 (2006) 1057-1071.

[29] F.S. Machado, T. Raghu, P. Sainam, R. Sinha, Software piracy in the presence of open source alternatives, Journal of the Association for Information Systems, 18 (2017) 3.

[30] F. Oberholzer-Gee, K. Strumpf, The effect of file sharing on record sales: An empirical analysis, Journal of Political Economy, 115 (2007) 1-42.

[31] L. Qiu, Q. Tang, A.B. Whinston, Two formulas for success in social media: Learning and network effects, Journal of Management Information Systems, 32 (2015) 78-108.

[32] F. Zhu, M. Iansiti, Entry into platform‐based markets, Strategic Management Journal, 33 (2012) 88-106.

[33] R.J. Kauffman, J. McAndrews, Y.-M. Wang, Opening the “black box” of network externalities in network adoption, Information Systems Research, 11 (2000) 61-82.

[34] B. Niu, L. Chen, Q. Li, F. Zeng, Restaurants’ Platform Partnership for Social Promotion and Resilient Revenue: Is Reward-Based Traffic Really Rewardful?, Production and Operations Management, (2024) 10591478231224919.

[35] H. Chesbrough, M. Bogers, Explicating open innovation: Clarifying an emerging paradigm for understanding innovation, New Frontiers in Open Innovation. Oxford: Oxford University Press, Forthcoming, (2014) 3-28.

[36] H.W. Chesbrough, Open Innovation: The new imperative for creating and profiting from technology, Harvard Business Press, 2003.

[37] E. Enkel, O. Gassmann, H. Chesbrough, Open R&D and open innovation: exploring the phenomenon, R&d Management, 39 (2009) 311-316.

[38] J. West, A. Salter, W. Vanhaverbeke, H. Chesbrough, Open innovation: The next decade, Research policy, 43 (2014) 805-811.

[39] M. Sacks, Competition between open source and proprietary software: Strategies for survival, Journal of Management Information Systems, 32 (2015) 268-295.

[40] A. Wormald, S.K. Shah, S. Braguinsky, R. Agarwal, Pioneering digital platform ecosystems: The role of aligned capabilities and motives in shaping key choices and performance outcomes, Strategic Management Journal, 44 (2023) 1653-1697.

[41] M. Mustonen, When does a firm support substitute open source programming?, Journal of Economics & Management Strategy, 14 (2005) 121-139.

[42] M.F. Niculescu, D. Wu, L. Xu, Strategic intellectual property sharing: Competition on an open technology platform under network effects, Information Systems Research, 29 (2018) 498-519.

[43] G. Parker, M. Van Alstyne, X. Jiang, Platform ecosystems, MIS Quarterly, 41 (2017) 255-266.

[44] G.G. Parker, M.W. Van Alstyne, Two-sided network effects: A theory of information product design, Management Science, 51 (2005) 1494-1504.

[45] R. Sen, A strategic analysis of competition between open source and proprietary software, Journal of Management Information Systems, 24 (2007) 233-257.

[46] G. Parker, M.W. Van Alstyne, Six challenges in platform licensing and open innovation, Communications & Strategies, (2009) 17.

[47] V. Mindel, L. Mathiassen, A. Rai, The sustainability of polycentric information commons, MIS Quarterly, 42 (2018) 607-632.

[48] E. Ostrom, Governing the commons: The evolution of institutions for collective action, Cambridge university press, 1990.

[49] H. Huang, G. Parker, Y.R. Tan, H. Xu, Altruism or Shrewd Business? Implications of Technology Openness on Innovations and Competition, MIS Quarterly, 44 (2020).

[50] A. Marton, I. Constantiou, G. Lagoudakos, Openness and legitimacy building in the sharing economy: An exploratory case study about CouchSurfing, (2017).

[51] X. Yi, Y. Fang, D. Wu, L. Jiang, BlockScope: Detecting and investigating propagated vulnerabilities in forked blockchain projects, arXiv preprint arXiv:2208.00205, (2022).

[52] J. Esber, S.D. Kominers, Why build in Web3, in: Harvard Business Review, 2022.

[53] B.M. Hill, A. Monroy-Hernández, The remixing dilemma: The trade-off between generativity and originality, American Behavioral Scientist, 57 (2013) 643-663.

[54] K. Lang, R. Shang, R. Vragov, Consumer co-creation of digital culture products: business threat or new opportunity?, Journal of the Association for Information Systems, 16 (2015) 3.

[55] G. Cheliotis, J. Yew, An analysis of the social structure of remix culture, in: Proceedings of the fourth international conference on Communities and technologies, 2009, pp. 165-174.

[56] A. Nagaraj, Does copyright affect reuse? evidence from Google books and Wikipedia, Management Science, 64 (2018) 3091-3107.

[57] H.L. Williams, Intellectual property rights and innovation: evidence from the human genome, Journal of Political Economy, 121 (2013) 1-27.

[58] L. Lessig, Remix: Making art and commerce thrive in the hybrid economy, Bloomsbury Academic, 2008.

[59] S. Spaeth, G. von Krogh, F. He, Research note—perceived firm attributes and intrinsic motivation in sponsored open source software projects, Information Systems Research, 26 (2015) 224-237.

[60] S. Faraj, G. von Krogh, E. Monteiro, K.R. Lakhani, Special section introduction—Online community as space for knowledge flows, Information systems research, 27 (2016) 668-684.

[61] D.W. Dahl, C. Fuchs, M. Schreier, Why and when consumers prefer products of user-driven firms: A social identification account, Management science, 61 (2015) 1978-1988.

[62] C.M. Fiol, E.J. O'Connor, Identification in face-to-face, hybrid, and pure virtual teams: Untangling the contradictions, Organization science, 16 (2005) 19-32.

[63] A. Prasad, V. Mahajan, How many pirates should a software firm tolerate?: An analysis of piracy protection on the diffusion of software, International Journal of research in Marketing, 20 (2003) 337-353.

[64] B.S. Butler, Membership size, communication activity, and sustainability: A resource-based model of online social structures, Information systems research, 12 (2001) 346-362.

[65] M.A. Chen, Q. Wu, B. Yang, How valuable is FinTech innovation?, The Review of Financial Studies, 32 (2019) 2062-2106.

[66] S. Chung, A. Animesh, K. Han, A. Pinsonneault, Financial returns to firms’ communication actions on firm-initiated social media: Evidence from Facebook business pages, Information Systems Research, 31 (2020) 258-285.

[67] J.W. Arts, R.T. Frambach, T.H. Bijmolt, Generalizations on consumer innovation adoption: A Meta-analysis on drivers of intention and behavior, International Journal of Research in Marketing, 28 (2011) 134-144.

[68] M.A. Stanko, Toward a theory of remixing in online innovation communities, Information Systems Research, 27 (2016) 773-791.

[69] A. Forsythe, G. Mulhern, M. Sawey, Confounds in pictorial sets: The role of complexity and familiarity in basic-level picture processing, Behavior research methods, 40 (2008) 116-129.

[70] A. Forsythe, N. Sheehy, M. Sawey, Measuring icon complexity: An automated analysis, Behavior Research Methods, Instruments, & Computers, 35 (2003) 334-342.

[71] A. Forsythe, M. Nadal, N. Sheehy, C.J. Cela‐Conde, M. Sawey, Predicting beauty: Fractal dimension and visual complexity in art, British journal of psychology, 102 (2011) 49-70.

[72] M.P. Da Silva, V. Courboulay, P. Estraillier, Image complexity measure based on visual attention, in: 2011 18th IEEE International Conference on Image Processing, IEEE, 2011, pp. 3281-3284.

[73] D.C. Donderi, Visual complexity: a review, Psychological bulletin, 132 (2006) 73.

[74] D.C. Donderi, An information theory analysis of visual complexity and dissimilarity, Perception, 35 (2006) 823-835.

[75] P. Böckerman, P. Ilmakunnas, Unemployment and self‐assessed health: evidence from panel data, Health Economics, 18 (2009) 161-179.

[76] F. Heyman, F. Sjöholm, P.G. Tingvall, Is there really a foreign ownership wage premium? Evidence from matched employer–employee data, Journal of International Economics, 73 (2007) 355-376.

[77] S. Chatterjee, A.S. Hadi, Regression analysis by example, John Wiley & Sons, 2015.

**Appendixes**

**Appendix A. Differences in mean before and after week-by-week Kernal PSM**

Table A1. Covariate differences in week 1

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.773 | 8.049 | -0.330 | 0.739 |  | 5.773 | 4.623 | 0.300 | 0.781 |
|  | -2.497 | -2.874 | 0.430 | 0.670 |  | -2.497 | -2.237 | -0.250 | 0.813 |
|  | 957.670 | 834.940 | 0.150 | 0.881 |  | 957.670 | 940.230 | 0.010 | 0.991 |
|  | 11.467 | 3.078 | 1.300 | 0.194 |  | 11.467 | 5.303 | 0.430 | 0.689 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A2. Covariate differences in week 2

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.773 | 8.026 | -0.360 | 0.720 |  | 5.773 | 5.025 | 0.190 | 0.858 |
|  | -2.497 | -2.834 | 0.420 | 0.675 |  | -2.497 | -2.651 | 0.210 | 0.845 |
|  | 599.670 | 991.270 | -0.410 | 0.680 |  | 599.670 | 404.690 | 0.310 | 0.775 |
|  | 11.173 | 5.028 | 0.640 | 0.525 |  | 11.173 | 3.010 | 0.620 | 0.577 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A3. Covariate differences in week 3

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 4.402 | 7.760 | -0.650 | 0.518 |  | 4.402 | 4.623 | -0.070 | 0.947 |
|  | -2.697 | -2.803 | 0.160 | 0.870 |  | -2.697 | -2.749 | 0.070 | 0.948 |
|  | 300.500 | 703.040 | -0.530 | 0.594 |  | 300.500 | 275.360 | 0.070 | 0.948 |
|  | 6.836 | 3.909 | 0.400 | 0.687 |  | 6.836 | 2.378 | 0.530 | 0.614 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A4. Covariate differences in week 4

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 4.655 | 7.452 | -0.650 | 0.516 |  | 4.655 | 4.849 | -0.050 | 0.960 |
|  | -2.697 | -2.762 | 0.100 | 0.917 |  | -2.697 | -2.649 | -0.060 | 0.956 |
|  | 358.750 | 992.580 | -0.720 | 0.469 |  | 358.750 | 447.120 | -0.150 | 0.888 |
|  | 7.277 | 6.952 | 0.030 | 0.977 |  | 7.277 | 4.319 | 0.260 | 0.807 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A5. Covariate differences in week 5

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 4.391 | 6.700 | -0.810 | 0.417 |  | 4.391 | 5.216 | -0.300 | 0.771 |
|  | -3.139 | -2.808 | -0.600 | 0.546 |  | -3.139 | -3.176 | 0.040 | 0.965 |
|  | 748.830 | 525.510 | 0.580 | 0.560 |  | 748.830 | 962.490 | -0.220 | 0.830 |
|  | 0.000 | 0.000 | - | - |  | 0.000 | 0.000 | - | - |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A6. Covariate differences in week 6

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.527 | 7.134 | -0.460 | 0.647 |  | 5.227 | 5.819 | -0.210 | 0.840 |
|  | -2.972 | -2.863 | -0.180 | 0.855 |  | -3.031 | -2.717 | -0.420 | 0.684 |
|  | 1265.700 | 367.210 | 2.340 | 0.020\*\* |  | 116.800 | 222.290 | -0.570 | 0.583 |
|  | 0.000 | 0.000 | - | - |  | 0.000 | 0.000 | - | - |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A7. Covariate differences in week 7

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.191 | 7.248 | -0.780 | 0.434 |  | 5.559 | 4.214 | 0.680 | 0.511 |
|  | -2.833 | -2.933 | 0.210 | 0.836 |  | -2.862 | -2.771 | -0.150 | 0.881 |
|  | 1574.000 | 509.360 | 2.690 | 0.007\*\*\* |  | 1427.500 | 873.220 | 0.540 | 0.600 |
|  | 6.833 | 4.548 | 0.330 | 0.742 |  | 7.687 | 3.144 | 0.630 | 0.541 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A8. Covariate differences in week 8

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.686 | 7.060 | -0.660 | 0.510 |  | 5.686 | 5.176 | 0.360 | 0.723 |
|  | -3.515 | -2.945 | -1.400 | 0.161 |  | -3.515 | -3.280 | -0.290 | 0.772 |
|  | 905.150 | 537.790 | 1.150 | 0.251 |  | 905.150 | 743.310 | 0.350 | 0.727 |
|  | 2.714 | 3.131 | -0.110 | 0.915 |  | 2.714 | 2.783 | -0.010 | 0.988 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A9. Covariate differences in week 9

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.689 | 7.241 | -0.790 | 0.427 |  | 5.689 | 6.026 | -0.790 | 0.427 |
|  | -3.491 | -2.960 | -1.410 | 0.158 |  | -3.491 | -3.529 | 0.040 | 0.970 |
|  | 1465.200 | 630.280 | 2.320 | 0.021\*\* |  | 1465.200 | 1531.400 | -0.070 | 0.948 |
|  | 3.643 | 3.414 | 0.050 | 0.961 |  | 3.643 | 3.024 | 0.160 | 0.877 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A10. Covariate differences in week 10

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.952 | 7.255 | -0.730 | 0.464 |  | 6.075 | 5.788 | 0.200 | 0.840 |
|  | -3.430 | -2.921 | -1.460 | 0.145 |  | -2.944 | -3.357 | 0.820 | 0.421 |
|  | 1177.300 | 527.230 | 2.090 | 0.037\*\* |  | 1253.800 | 749.160 | 0.860 | 0.399 |
|  | 4.683 | 5.596 | -0.080 | 0.938 |  | 4.995 | 5.656 | -0.070 | 0.948 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A11. Covariate differences in week 11

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.966 | 7.079 | -0.750 | 0.455 |  | 5.966 | 5.860 | 0.080 | 0.940 |
|  | -3.368 | -3.023 | -0.610 | 0.542 |  | -3.368 | -2.953 | -0.620 | 0.543 |
|  | 409.270 | 368.780 | 0.160 | 0.873 |  | 409.270 | 377.090 | 0.110 | 0.915 |
|  | 7.712 | 4.763 | 0.490 | 0.621 |  | 7.712 | 4.188 | 0.610 | 0.548 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A12. Covariate differences in week 12

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.349 | 7.336 | -0.500 | 0.614 |  | 6.349 | 6.595 | -0.170 | 0.864 |
|  | -3.503 | -2.979 | -0.940 | 0.349 |  | -3.503 | -3.123 | -0.530 | 0.602 |
|  | 218.400 | -0.250 | 0.805 | 0.873 |  | 218.400 | 222.720 | -0.020 | 0.982 |
|  | 1.291 | 4.477 | -0.590 | 0.556 |  | 1.291 | 1.009 | 0.150 | 0.881 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A13. Covariate differences in week 13

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.192 | 7.357 | -0.580 | 0.565 |  | 6.192 | -0.210 | 0.836 | 0.864 |
|  | -3.347 | -2.939 | -0.720 | 0.474 |  | -3.347 | -2.914 | -0.620 | 0.538 |
|  | 123.430 | 153.840 | -0.260 | 0.798 |  | 123.430 | 120.870 | 0.020 | 0.981 |
|  | 2.238 | 4.541 | -0.410 | 0.678 |  | 2.238 | 1.593 | 0.260 | 0.794 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A14. Covariate differences in week 14

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.947 | 7.176 | -0.730 | 0.466 |  | 5.947 | 6.123 | -0.130 | 0.897 |
|  | -3.389 | -2.947 | -0.840 | 0.401 |  | -3.389 | -2.931 | -0.730 | 0.471 |
|  | 102.440 | 150.100 | -0.380 | 0.705 |  | 102.440 | 88.963 | 0.200 | 0.846 |
|  | 2.558 | 3.947 | -0.280 | 0.782 |  | 2.558 | 2.047 | 0.150 | 0.882 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A15. Covariate differences in week 15

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.932 | 7.213 | -0.830 | 0.407 |  | 5.932 | 5.511 | 0.340 | 0.733 |
|  | -3.389 | -2.947 | -1.660 | 0.097\* |  | -3.484 | -2.876 | -1.210 | 0.234 |
|  | 178.000 | 145.100 | 0.320 | 0.745 |  | 178.000 | 337.390 | -0.630 | 0.531 |
|  | 2.855 | 4.717 | -0.350 | 0.728 |  | 2.855 | 2.376 | 0.170 | 0.869 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A16. Covariate differences in week 16

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.404 | 7.162 | -0.480 | 0.633 |  | 5.734 | 5.782 | -0.040 | 0.970 |
|  | -3.449 | -2.865 | -1.830 | 0.068\* |  | -3.510 | -2.885 | -1.220 | 0.232 |
|  | 891.330 | 208.780 | 4.890 | 0.000\*\*\* |  | 122.280 | 256.780 | -0.910 | 0.368 |
|  | 4.832 | 4.647 | 0.030 | 0.979 |  | 2.906 | 4.762 | -0.300 | 0.765 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A17. Covariate differences in week 17

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.404 | 7.162 | -0.820 | 0.414 |  | 5.734 | 5.782 | 0.250 | 0.806 |
|  | -3.371 | -2.943 | -0.980 | 0.329 |  | -3.371 | -2.992 | -0.740 | 0.465 |
|  | 408.590 | 240.650 | 0.940 | 0.346 |  | 408.590 | 348.060 | 0.190 | 0.850 |
|  | 7.039 | 4.248 | 0.540 | 0.592 |  | 7.039 | 3.768 | 0.590 | 0.557 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A18. Covariate differences in week 18

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.400 | 7.122 | -0.480 | 0.630 |  | 6.400 | 6.599 | -0.140 | 0.891 |
|  | -3.394 | -2.858 | -1.760 | 0.078\* |  | -3.394 | -3.202 | -0.380 | 0.708 |
|  | 376.300 | 214.590 | 0.840 | 0.402 |  | 376.300 | 484.870 | -0.210 | 0.838 |
|  | 3.874 | 4.960 | -0.190 | 0.846 |  | 3.874 | 3.479 | 0.100 | 0.918 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A19. Covariate differences in week 19

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.837 | 7.085 | -0.830 | 0.404 |  | 5.837 | 5.851 | -0.010 | 0.991 |
|  | -3.401 | -2.895 | -1.220 | 0.224 |  | -3.401 | -3.077 | -0.590 | 0.556 |
|  | 126.260 | 199.770 | -0.600 | 0.547 |  | 126.260 | 108.730 | 0.250 | 0.807 |
|  | 3.209 | 4.947 | -0.320 | 0.747 |  | 3.209 | 2.771 | 0.150 | 0.884 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A20. Covariate differences in week 20

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.508 | 6.724 | -0.140 | 0.886 |  | 6.508 | 6.485 | 0.020 | 0.984 |
|  | -3.322 | -2.825 | -1.640 | 0.102 |  | -3.322 | -3.395 | 0.120 | 0.908 |
|  | 360.870 | 194.110 | 1.290 | 0.198 |  | 360.870 | 238.460 | 0.400 | 0.691 |
|  | 0.000 | 0.000 | - | - |  | 0.000 | 0.000 | - | - |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A21. Covariate differences in week 21

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.647 | 6.634 | 0.010 | 0.992 |  | 6.647 | 6.642 | 0.000 | 0.997 |
|  | -3.419 | -2.925 | -1.210 | 0.226 |  | -3.419 | -3.037 | -0.780 | 0.439 |
|  | 124.580 | 152.580 | -0.280 | 0.783 |  | 124.580 | 103.930 | 0.330 | 0.742 |
|  | 0.000 | 0.000 | - | - |  | 0.000 | 0.000 | - | - |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A22. Covariate differences in week 22

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.310 | 6.702 | -0.310 | 0.754 |  | 6.365 | 6.065 | 0.260 | 0.799 |
|  | -3.646 | -2.853 | -2.780 | 0.006\*\*\* |  | -3.418 | -3.156 | -0.550 | 0.583 |
|  | 572.960 | 295.420 | 1.600 | 0.111 |  | 243.130 | 282.600 | -0.210 | 0.833 |
|  | 2.183 | 4.064 | -0.330 | 0.744 |  | 0.000 | 1.089 | -0.890 | 0.376 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A23. Covariate differences in week 23

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.168 | 6.875 | -0.630 | 0.527 |  | 6.046 | 5.959 | 0.080 | 0.934 |
|  | -3.494 | -2.870 | -2.460 | 0.014\*\* |  | -3.450 | -3.246 | -0.430 | 0.671 |
|  | 785.630 | 446.380 | 1.690 | 0.091\* |  | 575.100 | 706.720 | -0.370 | 0.710 |
|  | 0.855 | 9.545 | -0.690 | 0.490 |  | 0.882 | 2.467 | -0.260 | 0.793 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A24. Covariate differences in week 24

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.891 | 6.929 | -0.850 | 0.393 |  | 5.891 | 6.034 | -0.140 | 0.888 |
|  | -3.448 | -2.850 | -2.340 | 0.019\*\* |  | -3.448 | -3.408 | -0.070 | 0.944 |
|  | 331.770 | 401.210 | -0.370 | 0.713 |  | 331.770 | 330.450 | 0.010 | 0.995 |
|  | 0.500 | 8.290 | -0.870 | 0.383 |  | 0.500 | 1.240 | -0.240 | 0.810 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A25. Covariate differences in week 25

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.819 | 6.887 | -0.920 | 0.357 |  | 5.819 | 5.802 | 0.020 | 0.985 |
|  | -3.430 | -2.830 | -2.380 | 0.017\*\* |  | -3.430 | -3.300 | -0.260 | 0.798 |
|  | 192.060 | 347.630 | -0.930 | 0.352 |  | 192.060 | 168.900 | 0.270 | 0.788 |
|  | 2.497 | 7.331 | -0.510 | 0.611 |  | 2.497 | 2.333 | 0.070 | 0.942 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A26. Covariate differences in week 26

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.214 | 6.827 | -0.550 | 0.581 |  | 6.278 | 6.139 | 0.150 | 0.882 |
|  | -3.401 | -2.801 | -2.480 | 0.013\*\* |  | -3.179 | -3.038 | -0.390 | 0.700 |
|  | 504.910 | 350.670 | 0.930 | 0.352 |  | 519.910 | 509.510 | 0.030 | 0.977 |
|  | 2.680 | 6.071 | -0.390 | 0.698 |  | 2.761 | 2.920 | -0.060 | 0.954 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A27. Covariate differences in week 27

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.958 | 6.711 | -0.780 | 0.437 |  | 5.958 | 6.026 | -0.080 | 0.937 |
|  | -3.309 | -2.799 | -2.190 | 0.029\*\* |  | -3.309 | -3.119 | -0.430 | 0.667 |
|  | 520.640 | 354.950 | 1.050 | 0.295 |  | 520.640 | 638.040 | -0.330 | 0.739 |
|  | 1.924 | 6.620 | -0.540 | 0.588 |  | 1.924 | 2.281 | -0.180 | 0.854 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A28. Covariate differences in week 28

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.805 | 6.774 | -0.930 | 0.352 |  | 5.805 | 5.647 | 0.200 | 0.844 |
|  | -3.300 | -2.798 | -1.770 | 0.076\* |  | -3.300 | -2.887 | -0.970 | 0.338 |
|  | 490.260 | 259.920 | 1.770 | 0.077\* |  | 490.260 | 458.250 | 0.130 | 0.899 |
|  | 3.200 | 5.141 | -0.290 | 0.771 |  | 3.200 | 2.256 | 0.290 | 0.771 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A29. Covariate differences in week 29

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.737 | 6.811 | -1.090 | 0.278 |  | 5.737 | 5.649 | 0.110 | 0.909 |
|  | -3.331 | -2.787 | -2.480 | 0.013\*\* |  | -3.331 | -3.109 | -0.550 | 0.587 |
|  | 433.410 | 272.020 | 1.170 | 0.241 |  | 433.410 | 533.610 | 1.170 | 0.241 |
|  | 5.030 | 4.348 | 0.140 | 0.890 |  | 5.030 | 4.335 | 0.100 | 0.918 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A30. Covariate differences in week 30

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.885 | 6.803 | -0.960 | 0.335 |  | 5.885 | 5.874 | 0.010 | 0.989 |
|  | -3.329 | -2.753 | -2.770 | 0.006\*\*\* |  | -3.329 | -3.208 | -0.300 | 0.765 |
|  | 662.770 | 296.790 | 2.320 | 0.020\*\* |  | 662.770 | 681.120 | -0.050 | 0.959 |
|  | 7.030 | 4.862 | 0.280 | 0.778 |  | 7.030 | 11.437 | -0.250 | 0.806 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A31. Covariate differences in week 31

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.794 | 6.860 | -1.140 | 0.255 |  | 5.794 | 5.710 | 0.110 | 0.909 |
|  | -3.271 | -2.751 | -2.560 | 0.011\*\* |  | -3.271 | -3.159 | -0.290 | 0.770 |
|  | 173.260 | 219.070 | -0.390 | 0.697 |  | 173.260 | 166.860 | 0.060 | 0.950 |
|  | 2.654 | 3.543 | -0.220 | 0.822 |  | 2.654 | 2.482 | 0.050 | 0.961 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A32. Covariate differences in week 32

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.856 | 6.786 | -0.980 | 0.326 |  | 5.856 | 5.864 | -0.010 | 0.991 |
|  | -3.262 | -2.775 | -1.890 | 0.059\* |  | -3.262 | -2.971 | -0.760 | 0.449 |
|  | 111.760 | 190.820 | -0.680 | 0.494 |  | 111.760 | 88.096 | 0.670 | 0.503 |
|  | 2.217 | 3.252 | -0.340 | 0.733 |  | 2.217 | 1.716 | 0.290 | 0.773 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A33. Covariate differences in week 33

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.751 | 6.816 | -1.120 | 0.261 |  | 5.751 | 5.667 | 0.110 | 0.911 |
|  | -3.228 | -2.751 | -2.270 | 0.023\*\* |  | -3.228 | -3.109 | -0.310 | 0.757 |
|  | 123.300 | 167.420 | -0.520 | 0.604 |  | 123.300 | 114.080 | 0.150 | 0.880 |
|  | 1.924 | 2.662 | -0.240 | 0.811 |  | 1.924 | 1.715 | 0.090 | 0.926 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A34. Covariate differences in week 34

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.878 | 6.786 | -1.020 | 0.306 |  | 5.878 | 5.817 | 0.080 | 0.933 |
|  | -3.218 | -2.779 | -2.110 | 0.035\*\* |  | -3.218 | -3.108 | -0.290 | 0.771 |
|  | 165.560 | 204.430 | -0.340 | 0.737 |  | 165.560 | 161.130 | 0.040 | 0.966 |
|  | 2.539 | 2.781 | -0.080 | 0.938 |  | 2.539 | 2.501 | 0.010 | 0.992 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A35. Covariate differences in week 35

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.642 | 6.808 | -1.260 | 0.207 |  | 5.642 | 5.609 | 0.050 | 0.963 |
|  | -3.177 | -2.779 | -1.620 | 0.105 |  | -3.177 | -2.862 | -0.940 | 0.350 |
|  | 121.100 | 192.350 | -0.670 | 0.503 |  | 121.100 | 106.160 | 0.280 | 0.781 |
|  | 1.351 | 2.942 | -0.570 | 0.568 |  | 1.351 | 1.075 | 0.220 | 0.830 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A36. Covariate differences in week 36

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.559 | 6.722 | -1.410 | 0.157 |  | 5.533 | 5.741 | -0.300 | 0.766 |
|  | -3.571 | -2.762 | -4.010 | 0.000\*\*\* |  | -3.339 | -3.272 | -0.160 | 0.872 |
|  | 562.980 | 266.600 | 2.200 | 0.028\*\* |  | 224.130 | 360.830 | -0.620 | 0.534 |
|  | 0.844 | 2.676 | -0.790 | 0.431 |  | 0.643 | 0.759 | -0.160 | 0.870 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A37. Covariate differences in week 37

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.537 | 6.731 | -1.430 | 0.154 |  | 5.627 | 5.758 | -0.200 | 0.842 |
|  | -4.075 | -2.760 | -6.480 | 0.000\*\*\* |  | -3.657 | -3.641 | -0.030 | 0.973 |
|  | 372.420 | 207.280 | 1.680 | 0.093\* |  | 251.370 | 224.870 | 0.170 | 0.862 |
|  | 1.180 | 2.790 | -0.700 | 0.483 |  | 1.222 | 1.059 | 0.180 | 0.860 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A38. Covariate differences in week 38

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.503 | 6.683 | -1.410 | 0.158 |  | 5.592 | 5.659 | -0.100 | 0.919 |
|  | -4.092 | -2.808 | -5.300 | 0.000\*\*\* |  | -3.675 | -3.576 | -0.210 | 0.831 |
|  | 223.290 | 176.560 | 0.600 | 0.548 |  | 225.260 | 278.090 | -0.330 | 0.743 |
|  | 1.466 | 2.752 | -0.350 | 0.728 |  | 1.517 | 1.224 | 0.280 | 0.783 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A39. Covariate differences in week 39

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.323 | 6.713 | -1.700 | 0.089\* |  | 5.483 | 5.613 | -0.200 | 0.842 |
|  | -4.143 | -2.780 | -6.710 | 0.000\*\*\* |  | -3.625 | -3.628 | 0.010 | 0.993 |
|  | 112.900 | 151.040 | -0.490 | 0.623 |  | 117.570 | 122.130 | -0.080 | 0.939 |
|  | 1.107 | 2.564 | -0.570 | 0.566 |  | 1.164 | 1.160 | 0.000 | 0.998 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A40. Covariate differences in week 40

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.563 | 6.568 | -1.290 | 0.196 |  | 5.651 | 5.392 | 0.350 | 0.725 |
|  | -4.228 | -2.787 | -6.940 | 0.000\*\*\* |  | -3.829 | -3.746 | -0.180 | 0.861 |
|  | 193.070 | 155.300 | 0.350 | 0.726 |  | 199.390 | 178.180 | 0.150 | 0.885 |
|  | 0.665 | 2.488 | -0.870 | 0.387 |  | 0.688 | 0.813 | -0.130 | 0.899 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A41. Covariate differences in week 41

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.380 | 6.735 | -1.650 | 0.100 |  | 5.614 | 5.351 | 0.410 | 0.682 |
|  | -3.897 | -2.760 | -5.940 | 0.000\*\*\* |  | -3.543 | -3.424 | -0.330 | 0.742 |
|  | 57.889 | 94.438 | -0.770 | 0.444 |  | 59.817 | 53.931 | 0.250 | 0.805 |
|  | 1.187 | 1.786 | -0.380 | 0.707 |  | 1.246 | 0.930 | 0.330 | 0.744 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A42. Covariate differences in week 42

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.245 | 6.608 | -1.900 | 0.058\* |  | 5.430 | 5.353 | 0.130 | 0.898 |
|  | -4.413 | -2.831 | -8.020 | 0.000\*\*\* |  | -3.518 | -3.450 | -0.200 | 0.844 |
|  | 237.520 | 158.840 | 0.640 | 0.521 |  | 163.850 | 236.250 | -0.370 | 0.715 |
|  | 2.020 | 1.653 | 0.310 | 0.760 |  | 1.739 | 1.952 | -0.110 | 0.914 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A43. Covariate differences in week 43

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.351 | 6.685 | -1.770 | 0.077\* |  | 5.554 | 5.377 | 0.300 | 0.763 |
|  | -4.367 | -2.881 | -8.020 | 0.000\*\*\* |  | -3.832 | -3.757 | -0.170 | 0.866 |
|  | 138.930 | 201.770 | -0.450 | 0.656 |  | 146.700 | 168.940 | -0.170 | 0.864 |
|  | 1.327 | 2.094 | -0.420 | 0.678 |  | 1.403 | 1.234 | 0.110 | 0.913 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A44. Covariate differences in week 44

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.658 | 6.724 | -1.340 | 0.182 |  | 5.700 | 5.704 | -0.010 | 0.996 |
|  | -4.585 | -2.914 | -7.080 | 0.000\*\*\* |  | -3.972 | -3.904 | -0.140 | 0.889 |
|  | 244.670 | 221.790 | 0.150 | 0.883 |  | 260.160 | 242.080 | 0.080 | 0.933 |
|  | 0.760 | 1.313 | -0.540 | 0.589 |  | 0.809 | 0.756 | 0.080 | 0.937 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A45. Covariate differences in week 45

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.798 | 6.734 | -1.130 | 0.258 |  | 5.854 | 5.791 | 0.100 | 0.917 |
|  | -4.649 | -2.937 | -6.990 | 0.000\*\*\* |  | -4.434 | -4.315 | -0.210 | 0.831 |
|  | 232.030 | 151.500 | 0.830 | 0.409 |  | 235.480 | 180.430 | 0.390 | 0.700 |
|  | 1.499 | 1.574 | -0.070 | 0.942 |  | 1.521 | 1.505 | 0.010 | 0.990 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A46. Covariate differences in week 46

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.798 | 6.734 | -1.480 | 0.138 |  | 5.577 | 5.544 | 0.050 | 0.959 |
|  | -4.530 | -2.973 | -6.110 | 0.000\*\*\* |  | -4.530 | -4.431 | -0.180 | 0.858 |
|  | 64.778 | 105.120 | -0.750 | 0.453 |  | 64.778 | 59.599 | 0.170 | 0.869 |
|  | 0.303 | 1.655 | -1.260 | 0.208 |  | 0.303 | 0.331 | -0.050 | 0.958 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A47. Covariate differences in week 47

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 5.718 | 6.676 | -1.280 | 0.200 |  | 5.819 | 5.956 | -0.230 | 0.821 |
|  | -4.796 | -3.010 | -7.360 | 0.000\*\*\* |  | -4.462 | -4.439 | -0.040 | 0.966 |
|  | 232.360 | 96.575 | 2.100 | 0.036\*\* |  | 235.520 | 212.540 | 0.140 | 0.889 |
|  | 0.174 | 1.705 | -1.130 | 0.260 |  | 0.178 | 0.170 | 0.030 | 0.974 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A48. Covariate differences in week 48

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.064 | 6.622 | -0.760 | 0.447 |  | 6.026 | 5.972 | -0.230 | 0.821 |
|  | -4.617 | -3.049 | -6.000 | 0.000\*\*\* |  | -4.595 | -4.525 | -0.130 | 0.900 |
|  | 421.730 | 102.250 | 4.430 | 0.000\*\*\* |  | 265.420 | 224.980 | 0.270 | 0.784 |
|  | 0.258 | 1.464 | -1.100 | 0.272 |  | 0.262 | 0.258 | 0.010 | 0.992 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A49. Covariate differences in week 49

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.120 | 6.714 | -0.840 | 0.402 |  | 6.073 | 6.094 | -0.040 | 0.970 |
|  | -5.082 | -3.088 | -7.650 | 0.000\*\*\* |  | -4.686 | -4.504 | -0.360 | 0.719 |
|  | 510.940 | 133.290 | 3.600 | 0.000\*\*\* |  | 291.600 | 403.930 | -0.480 | 0.635 |
|  | 0.672 | 1.299 | -0.640 | 0.520 |  | 0.699 | 0.439 | 0.480 | 0.632 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A50. Covariate differences in week 50

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.154 | 6.748 | -0.850 | 0.395 |  | 6.154 | 6.140 | 0.030 | 0.979 |
|  | -4.954 | -3.115 | -7.030 | 0.000\*\*\* |  | -4.954 | -4.913 | -0.070 | 0.943 |
|  | 509.950 | 136.380 | 4.270 | 0.000\*\*\* |  | 509.950 | 440.640 | 0.270 | 0.785 |
|  | 0.292 | 1.219 | -1.180 | 0.239 |  | 0.292 | 0.186 | 0.380 | 0.702 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A51. Covariate differences in week 51

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.239 | 6.782 | -0.800 | 0.426 |  | 6.239 | 6.144 | 0.180 | 0.855 |
|  | -4.948 | -3.119 | -7.200 | 0.000\*\*\* |  | -4.948 | -4.808 | -0.270 | 0.785 |
|  | 214.390 | 89.526 | 2.550 | 0.011\*\* |  | 214.390 | 220.780 | -0.050 | 0.959 |
|  | 0.546 | 1.203 | -0.910 | 0.362 |  | 0.546 | 0.358 | 0.450 | 0.655 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A52. Covariate differences in week 52

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.118 | 6.816 | -1.040 | 0.300 |  | 6.118 | 6.035 | 0.160 | 0.871 |
|  | -4.825 | -3.130 | -6.780 | 0.000\*\*\* |  | -4.825 | -4.714 | -0.230 | 0.821 |
|  | 147.160 | 85.084 | 1.290 | 0.199 |  | 147.160 | 154.260 | -0.080 | 0.935 |
|  | 0.689 | 1.249 | -0.800 | 0.425 |  | 0.689 | 0.590 | 0.180 | 0.858 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A53. Covariate differences in week 53

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.352 | 6.727 | -0.550 | 0.581 |  | 6.352 | 6.254 | 0.170 | 0.862 |
|  | -5.082 | -3.161 | -7.440 | 0.000\*\*\* |  | -5.082 | -4.973 | -0.210 | 0.835 |
|  | 113.300 | 86.240 | 0.540 | 0.592 |  | 113.300 | 135.540 | -0.270 | 0.790 |
|  | 0.761 | 1.375 | -0.910 | 0.365 |  | 0.761 | 0.448 | 0.630 | 0.532 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A54. Covariate differences in week 54

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.321 | 6.752 | -0.620 | 0.535 |  | 6.277 | 6.287 | -0.020 | 0.986 |
|  | -5.219 | -3.153 | -7.840 | 0.000\*\*\* |  | -5.062 | -4.934 | -0.240 | 0.808 |
|  | 224.060 | 111.170 | 1.460 | 0.143 |  | 180.370 | 209.650 | -0.220 | 0.830 |
|  | 0.432 | 1.129 | -1.120 | 0.262 |  | 0.437 | 0.306 | 0.320 | 0.751 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A55. Covariate differences in week 55

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.321 | 6.752 | -0.490 | 0.626 |  | 6.385 | 6.409 | -0.040 | 0.969 |
|  | -5.029 | -3.174 | -7.120 | 0.000\*\*\* |  | -4.882 | -4.695 | -0.240 | 0.808 |
|  | 286.520 | 80.708 | 3.510 | 0.000\*\*\* |  | 78.163 | 137.770 | -0.840 | 0.402 |
|  | 0.484 | 1.241 | -1.010 | 0.315 |  | 0.495 | 0.411 | 0.180 | 0.856 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A56. Covariate differences in week 56

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.321 | 6.752 | -0.490 | 0.626 |  | 6.389 | 6.372 | 0.030 | 0.975 |
|  | -5.135 | -3.174 | -7.660 | 0.000\*\*\* |  | -5.135 | -5.005 | -0.240 | 0.809 |
|  | 286.520 | 80.708 | 1.520 | 0.129 |  | 194.410 | 173.740 | 0.170 | 0.862 |
|  | 0.350 | 1.158 | -1.180 | 0.239 |  | 0.350 | 0.161 | 0.740 | 0.463 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A57. Covariate differences in week 57

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.484 | 6.736 | -0.370 | 0.708 |  | 6.484 | 6.461 | 0.040 | 0.968 |
|  | -5.124 | -3.176 | -7.480 | 0.000\*\*\* |  | -5.124 | -4.955 | -0.330 | 0.745 |
|  | 183.020 | 108.100 | 1.020 | 0.309 |  | 183.020 | 230.540 | -0.330 | 0.744 |
|  | 0.631 | 1.210 | -0.920 | 0.356 |  | 0.631 | 0.256 | 0.810 | 0.417 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A58. Covariate differences in week 58

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.180 | 6.751 | -0.870 | 0.385 |  | 6.180 | 6.179 | 0.000 | 0.998 |
|  | -5.002 | -3.174 | -7.020 | 0.000\*\*\* |  | -5.002 | -4.895 | -0.200 | 0.845 |
|  | 57.716 | 89.737 | -0.440 | 0.663 |  | 57.716 | 57.955 | -0.010 | 0.992 |
|  | 0.755 | 1.292 | -0.760 | 0.448 |  | 0.755 | 0.481 | 0.450 | 0.657 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A59. Covariate differences in week 59

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.213 | 6.793 | -0.840 | 0.398 |  | 6.170 | 6.006 | 0.310 | 0.753 |
|  | -4.893 | -3.196 | -7.660 | 0.000\*\*\* |  | -4.739 | -4.595 | -0.300 | 0.766 |
|  | 44.809 | 79.196 | -0.670 | 0.502 |  | 40.659 | 40.873 | -0.010 | 0.989 |
|  | 0.346 | 1.097 | -1.070 | 0.284 |  | 0.350 | 0.264 | 0.250 | 0.802 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A60. Covariate differences in week 60

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.189 | 6.736 | -0.820 | 0.414 |  | 6.189 | 6.093 | 0.180 | 0.856 |
|  | -5.082 | -3.204 | -6.890 | 0.000\*\*\* |  | -5.082 | -4.862 | -0.410 | 0.679 |
|  | 154.720 | 90.994 | 1.330 | 0.185 |  | 154.720 | 188.460 | -0.330 | 0.743 |
|  | 0.264 | 1.177 | -1.360 | 0.173 |  | 0.264 | 0.214 | 0.190 | 0.853 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A61. Covariate differences in week 61

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.312 | 6.744 | -0.640 | 0.522 |  | 6.312 | 5.999 | 0.620 | 0.533 |
|  | -5.098 | -3.260 | -6.430 | 0.000\*\*\* |  | -5.098 | -4.860 | -0.440 | 0.662 |
|  | 89.256 | 83.019 | 0.100 | 0.918 |  | 89.256 | 93.483 | -0.060 | 0.949 |
|  | 1.068 | 0.996 | 0.130 | 0.898 |  | 1.068 | 1.155 | -0.110 | 0.912 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A62. Covariate differences in week 62

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.475 | 6.636 | -0.230 | 0.817 |  | 6.312 | 5.999 | 0.220 | 0.830 |
|  | -4.878 | -3.222 | -5.570 | 0.000\*\*\* |  | -4.878 | -4.645 | -0.420 | 0.673 |
|  | 123.590 | 119.350 | 0.050 | 0.964 |  | 89.256 | 93.483 | -0.100 | 0.917 |
|  | 0.000 | 0.000 | - | - |  | 0.000 | 0.000 | - | - |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A63. Covariate differences in week 63

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.475 | 6.636 | -0.400 | 0.687 |  | 6.474 | 6.375 | 0.170 | 0.867 |
|  | -5.100 | -3.221 | -6.380 | 0.000\*\*\* |  | -5.100 | -4.862 | -0.410 | 0.679 |
|  | 44.940 | 91.886 | 0.050 | 0.964 |  | 44.940 | 33.867 | 0.640 | 0.522 |
|  | 0.597 | 1.024 | -0.640 | 0.520 |  | 0.597 | 0.384 | 0.460 | 0.643 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A64. Covariate differences in week 64

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.287 | 6.836 | -0.400 | 0.687 |  | 6.287 | 5.888 | 0.780 | 0.437 |
|  | -5.055 | -3.252 | -6.310 | 0.000\*\*\* |  | -5.055 | -4.701 | -0.410 | 0.679 |
|  | 44.940 | 91.886 | -0.550 | 0.586 |  | 64.393 | 49.530 | 0.570 | 0.566 |
|  | 0.138 | 0.900 | -1.450 | 0.148 |  | 0.138 | 0.001 | 0.990 | 0.324 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A65. Covariate differences in week 65

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.412 | 6.752 | -0.510 | 0.610 |  | 6.371 | 6.243 | 0.230 | 0.820 |
|  | -5.100 | -3.276 | -6.120 | 0.000\*\*\* |  | -5.090 | -4.705 | -0.700 | 0.488 |
|  | 189.270 | 76.976 | 1.980 | 0.048\*\* |  | 71.534 | 128.780 | -0.910 | 0.365 |
|  | 0.534 | 1.085 | -0.850 | 0.394 |  | 0.540 | 0.289 | 0.600 | 0.552 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A66. Covariate differences in week 66

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.494 | 6.885 | -0.520 | 0.604 |  | 6.494 | 6.278 | 0.380 | 0.703 |
|  | -5.122 | -3.245 | -6.540 | 0.000\*\*\* |  | -5.122 | -4.920 | -0.340 | 0.732 |
|  | 58.918 | 66.104 | -0.170 | 0.862 |  | 58.918 | 53.798 | 0.190 | 0.847 |
|  | 0.627 | 1.012 | -0.690 | 0.492 |  | 0.627 | 0.392 | 0.480 | 0.635 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A67. Covariate differences in week 67

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.256 | 6.840 | -0.790 | 0.430 |  | 6.256 | 6.092 | 0.290 | 0.775 |
|  | -4.644 | -3.209 | -4.880 | 0.000\*\*\* |  | -4.644 | -4.271 | -0.690 | 0.491 |
|  | 37.000 | 45.429 | -0.350 | 0.723 |  | 37.000 | 27.022 | 1.060 | 0.289 |
|  | 0.328 | 0.943 | -1.080 | 0.282 |  | 0.328 | 0.225 | 0.310 | 0.757 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A68. Covariate differences in week 68

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.124 | 6.847 | -0.790 | 0.430 |  | 6.256 | 6.092 | 0.620 | 0.538 |
|  | -4.821 | -3.197 | -5.890 | 0.000\*\*\* |  | -4.660 | -4.327 | -0.690 | 0.493 |
|  | 28.600 | 37.836 | -0.690 | 0.488 |  | 28.899 | 25.684 | 0.460 | 0.648 |
|  | 0.117 | 1.260 | -1.770 | 0.077\* |  | 0.119 | 0.000 | 1.000 | 0.319 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A69. Covariate differences in week 69

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.388 | 6.949 | -0.780 | 0.436 |  | 6.388 | 6.204 | 0.340 | 0.738 |
|  | -4.926 | -3.184 | -6.170 | 0.000\*\*\* |  | -4.926 | -4.728 | -0.370 | 0.710 |
|  | 48.306 | 37.509 | 0.640 | 0.525 |  | 48.306 | 43.777 | 0.190 | 0.848 |
|  | 0.325 | 1.057 | -1.290 | 0.197 |  | 0.325 | 0.265 | 0.180 | 0.855 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A70. Covariate differences in week 70

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.238 | 6.941 | -1.010 | 0.315 |  | 6.197 | 5.803 | 0.670 | 0.501 |
|  | -5.000 | -3.216 | -6.190 | 0.000\*\*\* |  | -4.854 | -4.398 | -0.970 | 0.333 |
|  | 45.161 | 40.728 | 0.310 | 0.754 |  | 41.087 | 51.168 | -0.510 | 0.613 |
|  | 0.303 | 0.910 | -1.220 | 0.223 |  | 0.306 | 0.144 | 0.620 | 0.534 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A71. Covariate differences in week 71

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.367 | 6.904 | -0.760 | 0.450 |  | 6.428 | 6.010 | 0.810 | 0.418 |
|  | -4.905 | -3.167 | -6.380 | 0.000\*\*\* |  | -4.779 | -4.536 | -0.490 | 0.623 |
|  | 34.078 | 42.729 | -0.600 | 0.546 |  | 34.449 | 30.733 | 0.390 | 0.694 |
|  | 0.852 | 1.055 | -0.330 | 0.739 |  | 0.861 | 0.707 | 0.220 | 0.824 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A72. Covariate differences in week 72

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.312 | 6.893 | -0.800 | 0.422 |  | 6.312 | 6.066 | 0.460 | 0.645 |
|  | -4.839 | -3.168 | -5.930 | 0.000\*\*\* |  | -4.839 | -4.566 | -0.500 | 0.620 |
|  | 37.365 | 40.621 | -0.220 | 0.825 |  | 37.365 | 39.412 | -0.140 | 0.888 |
|  | 0.626 | 1.191 | -0.850 | 0.394 |  | 0.626 | 0.277 | 0.890 | 0.376 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A73. Covariate differences in week 73

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.318 | 6.931 | -0.860 | 0.387 |  | 6.318 | 6.044 | 0.510 | 0.609 |
|  | -4.976 | -3.184 | -6.430 | 0.000\*\*\* |  | -4.976 | -4.743 | -0.430 | 0.669 |
|  | 41.652 | 42.482 | -0.050 | 0.962 |  | 41.652 | 43.616 | -0.120 | 0.906 |
|  | 0.852 | 1.195 | -0.490 | 0.622 |  | 0.852 | 0.543 | 0.470 | 0.637 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A74. Covariate differences in week 74

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.073 | 6.709 | -0.950 | 0.344 |  | 6.116 | 5.848 | 0.350 | 0.730 |
|  | -5.046 | -3.190 | -6.510 | 0.000\*\*\* |  | -4.896 | -4.466 | -0.810 | 0.420 |
|  | 69.821 | 58.959 | 0.450 | 0.654 |  | 70.553 | 95.891 | -0.450 | 0.656 |
|  | 0.703 | 1.097 | -0.700 | 0.486 |  | 0.710 | 0.405 | 0.660 | 0.509 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A75. Covariate differences in week 75

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.189 | 6.840 | -0.920 | 0.360 |  | 6.142 | 5.952 | 0.320 | 0.748 |
|  | -4.674 | -3.149 | -5.760 | 0.000\*\*\* |  | -4.507 | -4.250 | -0.520 | 0.606 |
|  | 73.542 | 54.414 | 1.120 | 0.263 |  | 69.268 | 77.973 | -0.320 | 0.751 |
|  | 0.138 | 0.926 | -1.530 | 0.127 |  | 0.140 | 0.155 | -0.070 | 0.945 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A76. Covariate differences in week 76

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.440 | 6.921 | -0.630 | 0.528 |  | 6.395 | 6.125 | 0.400 | 0.686 |
|  | -4.674 | -3.149 | -5.570 | 0.000\*\*\* |  | -4.592 | -4.192 | -0.770 | 0.440 |
|  | 61.763 | 45.685 | 1.180 | 0.239 |  | 59.076 | 67.064 | -0.370 | 0.713 |
|  | 0.522 | 0.974 | -0.770 | 0.443 |  | 0.529 | 0.318 | 0.350 | 0.723 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A77. Covariate differences in week 77

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.368 | 7.030 | -0.860 | 0.392 |  | 6.368 | 6.255 | 0.180 | 0.855 |
|  | -4.787 | -3.099 | -5.840 | 0.000\*\*\* |  | -4.787 | -4.563 | -0.390 | 0.695 |
|  | 40.450 | 39.640 | 0.050 | 0.959 |  | 40.450 | 38.346 | 0.170 | 0.864 |
|  | 0.132 | 1.122 | -1.600 | 0.110 |  | 0.132 | 0.105 | 0.140 | 0.886 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A78. Covariate differences in week 78

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.511 | 6.985 | -0.640 | 0.525 |  | 6.511 | 6.064 | 0.820 | 0.412 |
|  | -4.659 | -3.127 | -5.210 | 0.000\*\*\* |  | -4.659 | -4.302 | -0.680 | 0.501 |
|  | 39.078 | 39.646 | -0.040 | 0.972 |  | 39.078 | 41.039 | -0.120 | 0.903 |
|  | 0.977 | 1.123 | -0.220 | 0.829 |  | 0.977 | 0.827 | 0.220 | 0.828 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A79. Covariate differences in week 79

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.489 | 7.067 | -0.720 | 0.474 |  | 6.385 | 6.239 | 0.230 | 0.819 |
|  | -4.776 | -3.048 | -6.470 | 0.000\*\*\* |  | -4.329 | -4.111 | -0.530 | 0.598 |
|  | 43.203 | 38.453 | 0.220 | 0.826 |  | 40.606 | 56.186 | -0.440 | 0.660 |
|  | 1.256 | 1.084 | 0.260 | 0.794 |  | 1.135 | 1.734 | -0.490 | 0.621 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A80. Covariate differences in week 80

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.188 | 6.971 | -0.960 | 0.339 |  | 6.260 | 6.000 | 0.380 | 0.706 |
|  | -4.885 | -3.041 | -6.260 | 0.000\*\*\* |  | -4.728 | -4.534 | -0.330 | 0.739 |
|  | 56.260 | 41.256 | 0.730 | 0.468 |  | 54.736 | 49.316 | 0.200 | 0.843 |
|  | 0.241 | 1.019 | -1.360 | 0.173 |  | 0.245 | 0.263 | -0.050 | 0.961 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

Table A81. Covariate differences in week 81

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Before matching | | | |  | After matching | | | |
| Variable | Mean treated | Mean control | t-statistics | p-value |  | Mean treated | Mean control | t-statistics | p-value |
|  | 6.218 | 7.178 | -1.240 | 0.216 |  | 6.223 | 5.957 | 0.510 | 0.614 |
|  | -5.136 | -3.116 | -7.220 | 0.000\*\*\* |  | -4.827 | -4.668 | -0.290 | 0.775 |
|  | 26.277 | 38.286 | -0.390 | 0.694 |  | 26.877 | 24.037 | 0.270 | 0.791 |
|  | 0.662 | 1.064 | -0.730 | 0.468 |  | 0.678 | 0.432 | 0.500 | 0.618 |

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1.

**Appendix B. Distribution of image complexity**

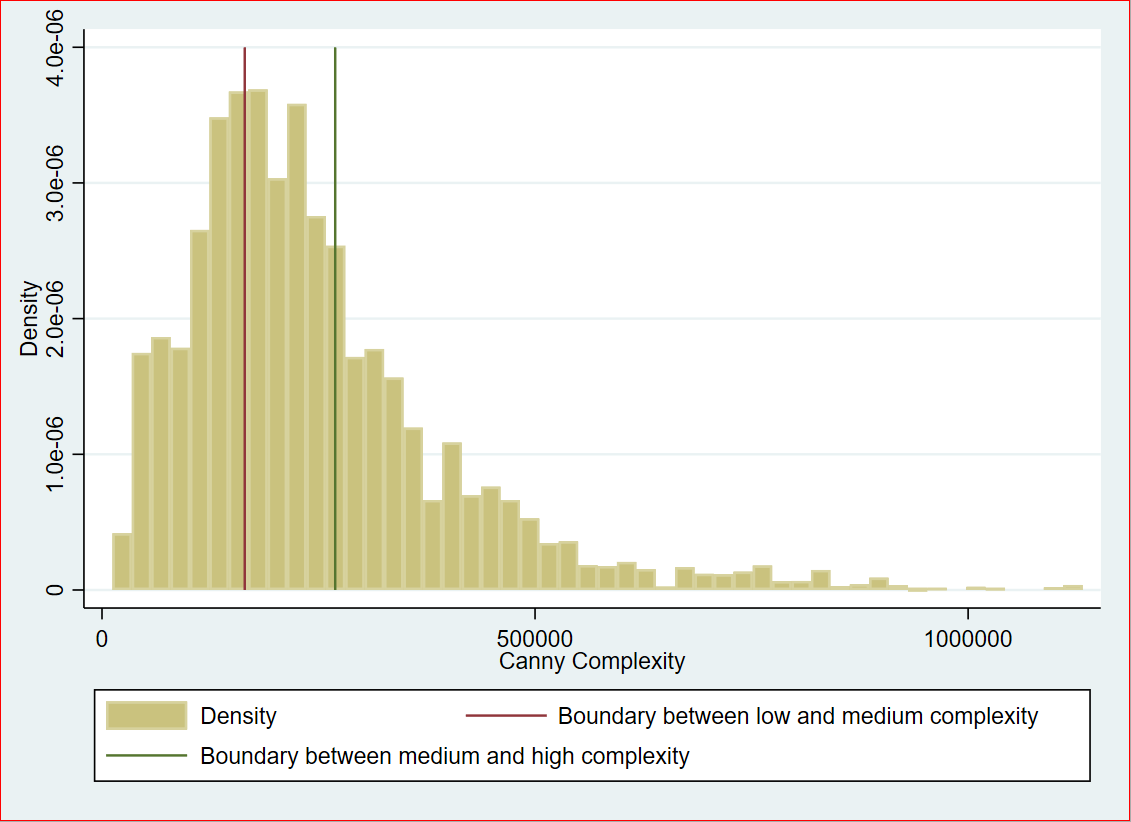


Figure B1. Distribution of Canny complexity

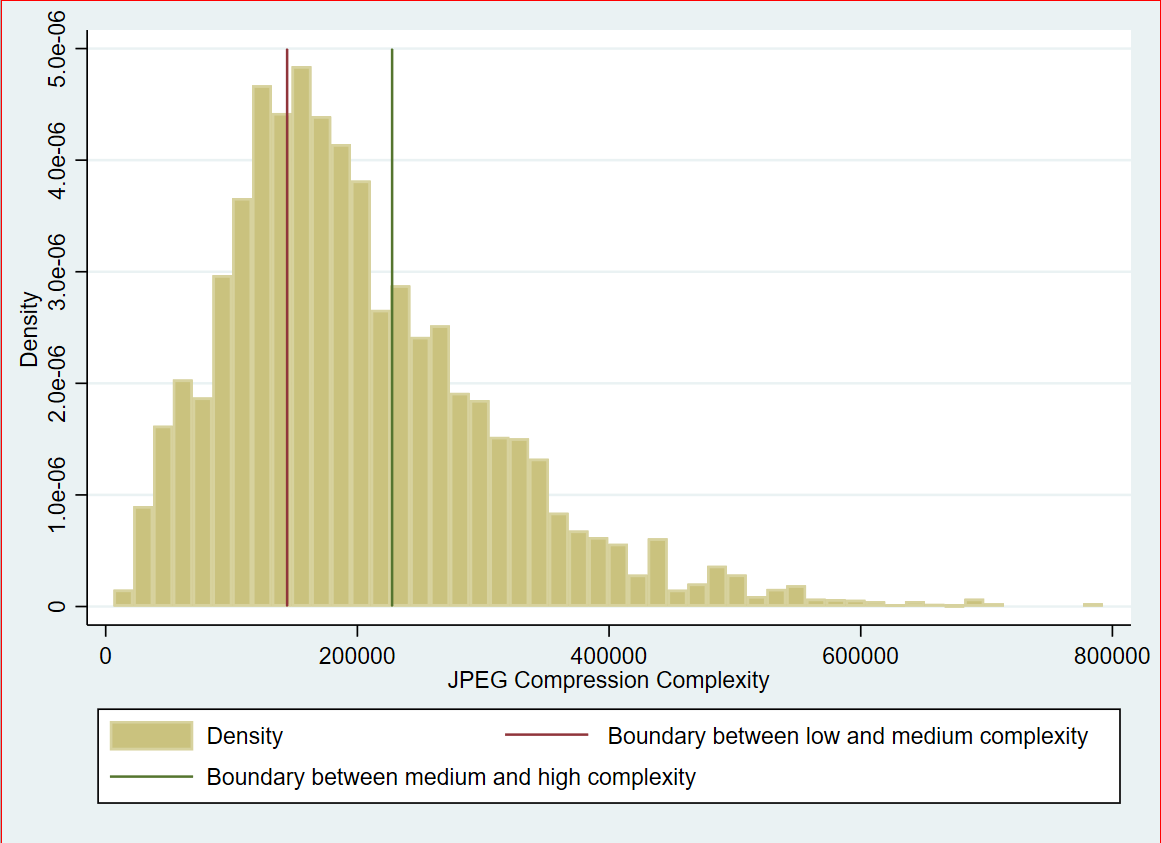


Figure B2. Distribution of JPEG compression complexity

**Appendix C.** **Multicollinearity test**

Table C1. Multicollinearity test

|  |  |
| --- | --- |
| Variable | VIF |
|  | 1.250 |
|  | 1.190 |
|  | 1.180 |
|  | 1.160 |
|  | 1.050 |
|  | 1.040 |
|  | 1.030 |
| Mean VIF | 1.130 |

1. https://www.okx.com/web3/marketplace/nft/stats/overview [↑](#footnote-ref-1)
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. [↑](#footnote-ref-2)
3. https://docs.nftgo.io/docs/listing-criteria [↑](#footnote-ref-3)
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. [↑](#footnote-ref-4)
5. The majority of NFT projects adopt the CC0 license to share the copyrights of artworks, placing these artworks into the public domain. Almost no NFT projects select other CC licenses. A small subset uses 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. [↑](#footnote-ref-5)