# Lending a Hand: Boosting Digital Asset Platforms Through Financial Flexibility

**(Authors' names blinded for peer review)**

*Key words*: NFT,

## 1. Terminology

We need to figure our what we want to call the financial feature, a simple name that we can use everywhere in the paper. Ideally, it would capture the following ideas: peer-to-peer, collaterizated by NFT, (any other characteristics)?

## 2. Introduction

Digital assets constitute a large market with a market cap of $2.3 trillion. Within this market, the sales of non-fungible tokens (NFTs) is growing at XX% year on year (include citation). The market for NFTs is similar to other investment goods such as art, real estate etc. in that each NFT is unique and often involves large monetary transactions. Having said this, NFTs differ from traditional investment goods in that multiple platforms compete for the trade of the same NFT, a few platforms dominate the NFT market, and crucially, unlike other goods, NFTs are secured and backed by digital asset collateral. The latter is especially relevant in that it makes financial lending feasible in this market. In this paper, we study the impact of availability of financial lending on the performance of a platform.

With the advent of newer payment gateways and payment mechanisms such as Buy Now Pay Later (BNPL), financial flexibility has become an increasingly important tool for a firm to increase its market share and performance. Desai and Jindal (2024) show that while adoption of financial lending tools such as BNPL can improve a firm's market share, its impact on prices is not as straightforward. In a market such as NFTs where multiple platforms compete to sell the same NFT, creating differentiation through other means such as offering financial lending can be decisive. Further, understanding how the availability of financial lending impacts different types of products or NFTs and different types of consumers is critical to assessing the success of financial lending. This paper attempts to address these questions. Specifically, we study (1) how does availability of financial lending impact sales, prices and time to sale of NFTs?, (2) does the effect of financial lending differ across different types of NFTs and consumers?, and (3) what is the mechanism underlying the changes in sales and prices due to available of financial lending?

Vi: I'm wondering how overall sales compare for Blur versus OpenSea. If Blur is much smaller, we could position around financial flexibility providing a competitive advantage to the underdog. Should think and talk next meeting. VS: Blur is a much younger platform and used to be a smaller platform but since 2023 its trading volume has been higher than opensea.

Vi: Make it clear that NFTs purchased on one platform can be sold on another platform. Might want to add a footnote explaining how this works, the audience is likely to have little idea.

The market for NFTs is dominated by four main players - Blur, Opensea, XX and XX, which collectively account for over XX% of all NFT sales. Out of these, Blur and Opensea are the biggest platforms with market shares of XX% and XX%, respectively. XX is the oldest platform and started operations in 20XX. By contrast, Blur started operations in 20XX but by 20XX, had a market share of XX%, most of which came from XX. Each NFT sold on these platforms belongs to a particular collection and a collection can have between XX and XX NFTs which may be priced anywhere between XX and XX USD. Between May 20XX and July 20XX, Blur enabled financial lending for 15 popular collections on its platform. For these collections, users (lenders) can offer collateralized loans to buyers with different repyament and interest rate options. Buyers of NFTs belonging to these collections can choose between different loan options or choose to not avail a loan altogether. Importantly, the loan is available for purchase of NFT only on Blur; the same NFT may be listed for sale on other platforms but without the option of a loan. In our data, we have detailed user level information on trades and observe the sales of all NFTs belonging to all collections (regardless of availability of financial lending) before and after the availability of financial lending on the four major platforms.

We measure outcomes at the collection level since the policy change or treatment (introduction of financial flexibility) by the focal platform (Blur) occurs at this level. We discuss the outcomes for both Blur and the primary competitor, OpenSea. X collections out of a total of Y were treated by Blur over the time frame DATE to DATE. We analyze the impact of financial lending by comparing the focal collections with other collections belonging to the same genre. To account for differences in treated and untreated collections, we use a synthetic difference-in-difference approach which allows us to compare like collections.

First, examining unit sales (quantity), we find that there is an increase in unit sales at the focal platform Blur, but not at the primary competitor platform, OpenSea. When we look at the overall revenue at each of the platforms, we find that the revenue at Blur increased due to the treatment, as did the revenue at OpenSea (in some but not all of the DID specifications). Further, we find that availability of financial flexibility lowers the time to sell for the treated collections, on average, by XXX hours on Blur (relative to OpenSea), but does not have any impact on the prices of these collections.

One possible reason for the increase in sales of the treated collections at Blur could stem from an increase in the number of listings of NFTs belonging to these collections. Indeed, we do find that the number of listings of the treated collections increased on Blur, but there was no significant change in the number of listings at OpenSea. We also examine whether the availability of financial flexibility at the focal platform leads to new user acquisition, and find that there was no incremental user acquisition, indicating that the platform did not become more attractive to those outside the market (or extensive margin). This is likely because the platform did not advertise to new users or otherwise promote this newly available feature $\Longleftarrow$ VerifyVS: Platform advertise it through Twitter, not sure if we can state this. However, we find that the introduction of financial flexibility increased the activity among existing users at Blur. Further, among the treated collections, multi-homing users who are present on both platforms, increased their share of wallet at Blur relative to OpenSea. These last two results are especially important because they show that offering financial flexibility can increase engagement among a platform's existing user base. These results are robust to the possibility of a spillover (substitution effect) from the treatment to control group.

To further understand the source of the increase in sales, we divide NFTs in each collection into two groups - the top 20% and the bottom 80% based on their pre-financial flexibility selling price. We find that almost all of the increase in sales can be attributed to an increase in the sales of the top 20% NFTs, with the bottom 80% NFTs showing a marginally significant increase in sales. We also find that the number of listings increased for all NFTs and not just the top 20% NFTs, and that the price of none of these NFTs changed post the availability of financial flexibility. Combined with the fact that the most expensive NFTs are also more rare (higher quality), the disproportionate increase in sales of these NFTs represents "flight to quality" wherein offering financial flexibility resulted in existing users purchasing more better quality (more rare and expensive) NFTs. These results are robust to different (i) methodologies (standard DiD, staggered DiD and synthetic DiD), (ii) control groups, and (iii) types of users in the control groups.

This paper contributes to the recent literature on platform performance and the impact of financial flexibility. To the best of our knowledge, this is the first paper to show how the availability of financial flexibility impacts platform outcomes and user behavior by both sellers and buyers in a market where platforms sell unique SKUs $\Longleftarrow$ Verify VS: some collections may have multiple tokens of the same type so we should probably omit the term unique and compete for the same consumers. Our data allow us to explore the role of both supply side and demand side considerations in influencing NFT sales and prices. Second, the result that financial flexibility leads to a "flight to quality" is novel and shows that financial flexibility has a disproportionate impact on higher quality NFTs. Given the competitiveness of the NFT market, and the fact that all platforms sell identical SKUs, the results point to the importance of financial flexibility as a tool to increase revenues.

The rest of the paper is organized as follows. Section 2 discusses the different streams of literature this study builds on and contributes to. Section 3 provides an overview of the setting and describes the data. Section 4 provides the main results on the impact of financial flexibility on platform and consumer outcomes. Section 5 explores the underlying mechanisms, and Section 6 concludes.

### 2.1. Results

We obtain results using three variants of difference-in-differences: baseline DiD, Staggered DiD and Synthetic DiD. Note that in all cases, the standard errors were clustered at the collection level ⟸ Verify-VS: In all the DID specifications, the algorithms allow for clustering by group variable (collection). In other specifications where we have interaction analysis, the errors are clustered by collection and week.. The analysis done here supports (a), but I don't think it provides evidence to support (b). Should think about whether we want to make this claim or not. All model specifications included fixed effects at the collection and week levels.

Overall, the results show a marked increase in activity, unit sales and revenues across the focal platform after financial flexibility was introduced, with respect to two reference points: (a) the focal platform before treatment, and (b) the primary competitor after treatment.

Questions:

1. What is the economic significance of the results? Would be useful to include that in the above paragraphs.

2. Are SEs clustered at the collection level? Time period level? Need to verify and confirm.VS: SE are clustered by collection in the Did models, and by collection and week in the fixed effects model

3. Should we do this as a bivariate model? RevenueBLUR and RevenueOpenSea together accounts for the correlation, and might simplify reporting the results and reduce the number of tables. VS: We will need to do interaction analysis for this - the DID models we use do not allow for it (the rationale being the effect is computed for each cohort seperately and then aggreated). In the fixed effect analysis we run the analysis for Opensea and Blur together.

4. How are active users defined? Might want to include that here.VS: Active users are defined as number of unique users who performed one or more trade in the given week.

### 2.2. Relevant Papers

1. Credit Supply and House Prices: Evidence from Mortgage Market Segmentation: `https://www.nber.org/system/files/working_papers/w17832/w17832.pdf`

2. Digital Collateral: `https://academic.oup.com/qje/article-abstract/139/3/1713/7588833`

3. The Effect of Mortgage Credit Availability on House Prices and Construction: `https://pages.stern.nyu.edu/~ahizmo/ahkm.pdf`

Comment [Vineet]: I was thinking more about why the peer-to-peer lending works well here for BLUR, but would not work for say Amazon marketplace (or most other platforms). The NFT product has some unique characteristics, which are: (a) digital, (b) ownership is recorded and transferable by the platform (correct this point if it is incorrect). These characteristics allow the loan to be collateralized (not sure if that's a word). This is likely to reduce default. Unlike in Prosper, where there is a much higher risk, because the loans are not backed by collateral.

Literature: It would be helpful to add some papers related to the following: (a) Financial flexibility with regular (non-platform purchases e.g. financing, BNPL etc), (b) peer-to-peer lending (Prosper etc.). (c) Platform making loans (e.g. Alibaba?).

Implications: Applicable to digital assets/ ownership (examples?- stocks), which enables collateralization. Cost is collateralization here, in platforms like Amazon the cost could be related to credit score.

Note: The ownership here is independent of the platform.

## 3. Discussion 4th March

Main results: Collections treated with financial flexibility see an increase in unit sales and revenue. The time to sell for the treated collections goes down, but we do not see any impact on prices.

For collections treated with financial flexibility, we see an increase in sales quantity among existing customers of the collection, but has no impact for customers new to the collection. Relative to competition, the share of wallet for collections on the focal platform increases.

There could be a plausible spillover effect (substitution) from the treatment to control group – our analysis is robust to such possibility.

Should we separate out control group versus treated group?

Heterogeneity/Mechanism: The sales increase significantly for the Top20 expensive/ rare NFT(s), and marginally significant for the Bottom 80.

The effect on Sales is driven largely by the top most expensive NFT(s) of the treated collection. There is a disproportionate impact of financial flexibility on the expensive NFT(s), and the price does not seem to change. On Opensea, the impact is less clear in terms of quantity sold.

The sales for the top 20 could be increasing as the listing of the top 20 is increasing. However, we find that listings of both the top 20 and bottom 80 are increasing.

Financial flexibility as a flight to quality. Parallel shift in supply.

Results are robust to different specifications of (a) DID, and (b) control groups, and (c) users in control groups.

### 3.1. Positioning

**Positioning A:** Financial flexibility is known to be important across many markets. Recent innovations include BNPL. However, while it has been studied in product markets, the impact of financial flexibility on participants in multi-sided platforms has not been studied. We have a unique context: (a) some subsets of the products are treated with financial flexibility on a platform, (c) the competing platform does not offer financial flexibility (b) data from the focal and a competing platform, selling the same set of products, (d) data at user, collection and platform level.

Pros: Financial flexibility is present in many markets Who is bearing financial risk? Is it the platform? Buyers / Sellers? Buyers / Sellers

Cons: Other papers might have done this. People have studied lending quite a bit, so this might not be viewed as novel.

**Positioning B:** NFTs are growing - big market, multiple platforms. Consumers face a lot of uncertainty in prices and demand now and in the future. One crucial factor which can determine the growth of NFTs is access to credit. In this paper, we want to understand how access to financial flexibility impacts the buyer and seller behavior including outcomes such as sales and prices, at the focal platform as well as the competing platforms.

Pros: Big and interesting market - very topical Can focus on the particular features of NFT market, can tap into interest in the market. What makes it different and interesting?

Cons: Results very focused - generalizability of what? (collateralization) How is this different from lending for houses? (Availability of mortgages) Other ways to grow the NFT market? Why only study financial lending?

**Positioning C:** Digital assets have certain properties. 1) Trade through multiple platforms. Active community of buyers and sellers. 2) Unlike physical goods, digital assets are unique and can be collaterized by the platform.

How different from property market? Art market? Efficient to provide NFT as collateral, because ownership claims are directly documented by the platform.

How similar is this to peer-to-peer lending? Similar to prosper.

Pros:

Cons:

### 3.2. Positioning

Digital assets have a large market cap 2.3 trillion. Fintech? Impact of Fintech on Digital Asset Markets Digital assets (NFT) market is big and growing. The market is served / dominated by a small number of platforms competing to connect buyers and sellers of digital assets. Interested in studying the role of fintech / financial lending as a platform strategic choice and flexibility on market equilibrium outcomes. Why is differentiate from Uber introducing financing? 1) Investment Goods 2) Transactions are large in monetary terms 5) Peer-to-peer unregulated loans (not made by the platform), 4) Secured or Backed by Digital Asset Collateral making lending feasible (need to play this angle up, low defaults)

How is it similar to other contexts? Competition between Platforms is important in lot of different empirical settings?

https://www.statista.com/outlook/dmo/fintech/united-states

Can you buy something on OpenSea and sell it on Blur? What makes our setting different?

1. Role of Competition and adoption of credit by one firm rather than for all firms (mortgage). Policy in housing is at a market level.
2. P2P lending versus mortgage lending by banks (but compares to Prosper then...)
3. Dual role of individual as a consumer and a lender?

What tools can a platform use to grow?

### 3.3. Possible Titles

1. Does Enabling Financial Flexibility provide a competitive advantage?
2. Does Enabling Financial Flexibility help digital asset platforms?
3. "The Impact of Financial Flexibility on Digital Asset Platforms"
4. "Financial Flexibility: A Catalyst for Growth in Digital Asset Platforms?"
5. "Enhancing Digital Asset Platforms Through Financial Flexibility"
6. "The Role of Financial Flexibility in the Success of Digital Asset Platforms"
7. "Unlocking Potential: Financial Flexibility in Digital Asset Platforms"
8. "How Financial Flexibility Shapes the Future of Digital Asset Platforms"
9. "Financial Flexibility and Its Influence on Digital Asset Platform Performance"
10. "The Benefits of Financial Flexibility for Digital Asset Platforms"
11. "Financial Flexibility: Key to Robust Digital Asset Platforms?"
12. "Financial Adaptability: Boosting Digital Asset Platforms"
13. Lending a Hand: Boosting Digital Asset Platforms Through Financial Flexibility
14. Lending a Hand: Does Financial Flexibility Boost Trading Activity on Digital Asset Platforms
15. Liquidity Unleashed: The Effects of Financial Flexibility on Digital Asset Trading
16. The Flexibility Premium: How Peer-to-Peer Lending Affects Digital Asset Prices and Trading Activity

17. From Illiquidity to Opportunity: The Role of Financial Flexibility in Digital Asset Platforms

18. The Interplay Between Liquidity Provision and Market Efficiency: A Study on the Impact of Peer-to-Peer Lending on Digital Asset Platforms

19. "Flex Your Finances: Empowering Digital Asset Platforms"

20. "Financial Freedom: Supercharging Digital Asset Platforms"

21. "Digital Fortunes: The Power of Financial Flexibility"

22. "Financial Fluidity: Revolutionizing Digital Asset Platforms"

23. "The Flex Factor: Elevating Digital Asset Success"

24. "Fluid Finances: Boosting Digital Assets to New Heights"

### 3.4. Final Positioning

Digital assets are a large and growing industry, and their trade is facilitated by several platforms. These products can be expensive, ranging in price from X to Y. Many consumers are not able to afford or have liquidity to purchase these assets, without access to financing. However, traditional lenders like banks typically do not finance purchase of digital assets (CITE) for XYZ reasons.

Hence, digital asset platforms introduce peer-to-peer lending for purchasing these assets. They do not bear risk for these loans, and the unique feature of digital assets is that they can be completely collateralized (explain why).

We examine the value of a platform introducing precisely such a form of financial flexibility, by enabling peer-to-peer marketplace for loans of these assets.

Market value of digital assets doubled from $830 billion to $1.6 trillion in 2023.

## 4. Research Question

We study the impact of platform-led initiative of financial flexibility, in the form of collateralized loans, on sales, revenue, and user behavior. This is a novel setting where, instead of a third party, the platform itself facilitates peer-to-peer lending, for buying the products on the platform. Given the recency of the phenomena, the efficacy of such a peer-to-peer, platform-led lending strategy on its performance is unclear[1] and understudied. Assessing the outcome will inform a platform's strategies in incorporating such schemes for their users.

The net outcome of the above-discussed strategy is unclear due to the reasons such as: (i) If users themselves are involved in lending, their purchase capabilities may be restricted, thus, creating a negative impact on the sale, (ii) The net outcome may also depend upon whether users complement or substitute their own budget with this additional flow of cash. (iii) The strategy may also impact the assortment of products (or nfts) available on the platform, which may subsequently impact the sales and prices of the NFT(s).

Plausible Mechanisms:

1. **Advertisement Effect:** If the Advertisement effect would be at play we should see a positive effect on the sales of BNPL-enabled collections on both platforms (Opensea and blur). This could also lead to market expansion, as more new users will be entering the market. We do not see any of these effects which helps us rule out the advertisement effect (reference tables)

2. **Income Effect:** If the Income Effect is at play we should find that people buy more, by supplementing their own budget with the additional income source.

3. **Competition Effect:** The availability of BNPL on Blur may have a significant effect on users' multihoming tendencies. This is a setting where both the switching cost and multihoming cost of users are significantly low, thus users may gravitate towards Blur from Opensea.

4. **Supply Side:** Change in the availability of more NFT(s) , i.e., increased liquidity

# 5. To Do:

## 5.1. To do in Data

- Outcome: Revenue, (Total) Users, Exclusive Users, Expenditure per user, Quantity, Price, Time to sell

1. Compute outcome variables per collection and plot a **stacked histogram** across collections. Show treated and non-treated collections with different colors (red/blue). Can also plot as transparent with 2 separate histograms.

[1] See https://blockworks.co/news/nft-loans-on-blur

2. Plot outcome variables for each collection over time, and show when the collection was treated. Show before and after. (a) Figure with all treated collections (15 collections) normalized by average sales for that collection. (b) Average of all treated collections. (c) Figure with selection collection that makes the point that treatment with BNPL has a substantial impact.

3. X variables: Rarity distribution across collections, Histogram of mean and histogram of coefficient of variation, stacked histogram for treated and non-treated collections.

4. Split up top 20% and bottom 80% and show for above analysis.

5. Do this for all the X variables.

6. User level analysis: Distribution of total users, exclusive users across collections.

### 5.2. To do in Analysis

1. Need to include a subsection on threats to SUTVA

2. Validation that chosen control group is reasonable and appropriate to examine the questions we are asking. Specific metrics that show this point clearly. Also need to have robustness.– Parallel Trend Assumption

3. Option 1: Reorganize Table 3 and other tables, so that we have only one specification and transpose.

4. Option 2: Show table with one outcome variable and all specifications.

5. Can show model without the fixed effects and controls. Are there any controls beyond ?

6. Need to have model equation (complete model specification) that is being estimated.

7. Mechanism first, then robustness (including robustness to mechanism)

## 6. Data and Model

The objective of our study is to assess the impact of BNPL on market efficiency and revenue for the NFT collections. To investigate our research questions, we focus on two major NFT platforms- Blur and Opensea. Blur was launched in October 2022 and became the leading trading platform for NFTs by volume (dat 2023). As of November 2023, Blur accounts for an all-time trade volume of $6.85 billion. Opensea is one of the oldest NFT trading platforms and accounts for an all-time trade volume of $36.22 billion.[2]

**Institutional Details:** Starting May 2023, Blur introduced a policy referred to as *Buy Now, Pay Later (BNPL)* feature for a few collections in a staggered manner. The policy involved: (i) Lending against NFTs eligible for BNPL, (ii) Customers can also choose to pay for their NFT purchases in full later or break up the cost into multiple payments over a set period of time. This can be a convenient option for those who may not have the funds available to make a large NFT purchase upfront but still want to invest in these digital assets. The policy was rolled out in a staggered manner for different collections during the period May 2023- December 2023.

BNPL was enabled by BLUR for collections with dominating the market capitalization in the PFP category. To construct the control group, we used top NFT collections from other categories, such as Art, Gaming, and Membership. Figure 1 presents the treatment variation heatmap for the collections in our sample. Each row represents a collection, and each column represents a week from our dataset. Thered area represents treated collection-week observations, whereas the blue area represents the untreated collections in a given week. The collections for which BNPL was enabled by Blur, their respective timeline of treatment, and the control collections are presented in Table 1. We also provide the average weekly sale, collection size, and active users for these collections. We identified the launch dates of collections implementing the BNPL feature, primarily through BLUR Twitter announcements.[3] The same collections were traded on other platforms like Opensea without any financial flexibility such as BNPL.

[2] "https://dappradar.com/rankings/nft/marketplaces"

[3] "https://twitter.com/blur_io"

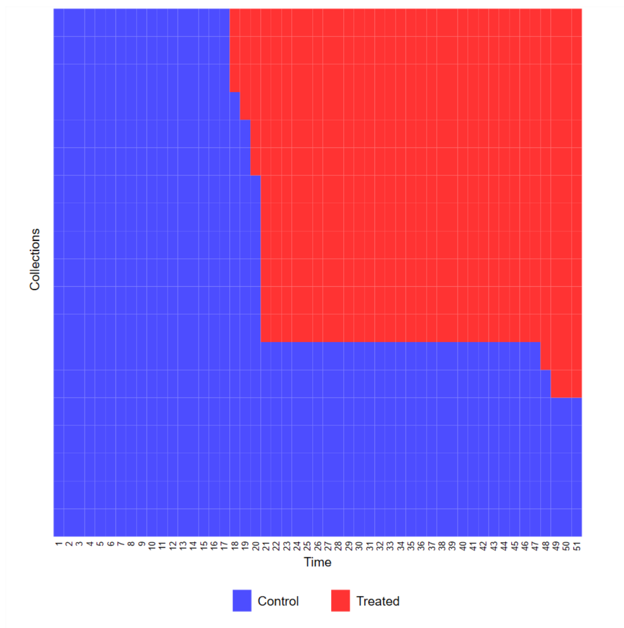



**Figure 1** **Treatment Variation Plot**

**Table 1** **BNPL Enabled Collections and Control Group.**

| Collection | BNPL Week(2023) | Avg Sale | Collection Size | Active Users |
|---|---|---|---|---|
| Azuki | 18 | 657.59 | 10,000 | 10768 |
| Beanzofficial | 21 | 1931.13 | 19,950 | 24370 |
| Bored-ape-kennel-club | 21 | 338.26 | 9,602 | 8756 |
| Boredapeyachtclub | 20 | 174.53 | 9,998 | 5610 |
| Clonex | 21 | 612.86 | 19,593 | 11222 |
| Kanpai-pandas | 21 | 145.58 | 7,962 | 5313 |
| Degods | 19 | 555.92 | 8,989 | 8333 |
| Milady | 18 | 552.59 | 9,733 | 12185 |
| Mutant-ape-yacht-club | 20 | 521.43 | 19,493 | 15446 |
| Otherdeed | 21 | 3011.62 | 45,920 | 23345 |
| Pudgypenguins | 21 | 382.30 | 8,888 | 9567 |
| Remilio-babies | 21 | 1406.91 | 9,172 | 12967 |
| Moonbirds | 48 | 634.28 | 9,999 | 9111 |
| Lilpudgys | 49 | 824.84 | 21,653 | 19310 |
| **Control Groups** | | | | |
| Art (14 collections) | 0 | 1427.32 | | 9122 |
| Gaming (12 collections) | 0 | 143.21 | | 2921 |
| Membership (15 collections) | 0 | 919.98 | | 2076 |
| Meebits | 0 | 273.24 | 19,999 | 6024 |
| Doodles | 0 | 548.83 | 9,998 | 8627 |

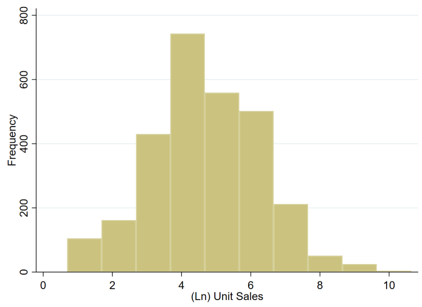
Our data spans the January - December 2023 period, i.e., 52 weeks. The transaction data is compiled for 57 top NFT collections by market capitalization across the treatment and control groups belonging to PFP, Art, Gaming, and Membership categories. Each collection has a unique

ID, referred to as Collection ID hereafter. Within a collection, there are multiple NFT(s), referred to as token ID hereafter. We collected daily data on users' NFT trading activities across Blur and Opensea using Opensea and other third-party API(s). We then aggregate our data to a weekly level for the purpose of our analysis. The rationale for aggregating the unit of data from daily to weekly is to overcome bias in the significance of the estimation due to a large sample (e.g., Kaplan et al. 2014). We avoid monthly aggregation because it would result in a very small number of observations for each group in the sample. This would not provide a meaningful sample, particularly regarding the number of observations per clustered group (i.e., collection) (Cameron and Miller 2016, Abadie et al. 2022).

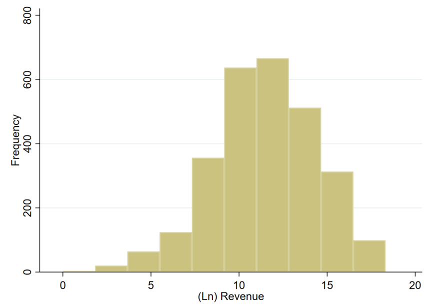
To assess the impact of BNPL on the treated collections' performance, we rely on measures such as unit sales, prices, and overall revenue (calculated in USD), following prior studies such as such as Ataman et al. (2010), Lam et al. (2001). Specifically, we collate details of every transaction for the 57 NFT collections, including collection and token ID, time of sale, buyer and seller identity, price of sale, and platform of sale. We also identify and eliminate wash trades from our sample.[4] The distribution of our primary variables of interest, i.e., unit sales, prices, and revenue across collections, is presented in Figure 2 and is seen to be following a log-normal distribution. The distribution of unit sales, prices, and revenue across the different NFT categories is shown in Figure 3.

We also collect data on new and active users to assess the underlying mechanisms related to market expansion and advertisement effects. Moreover, to examine the availability of NFT(s) for sale, we aggregate data on users listing behavior. Further, we classify the NFT(s) within a collection based on their past selling price (before the launch of BNPL) and rarity, which enables us to examine the differential impact of BNPL on NFT(s) within a collection. For instance, we collected information on the rarity ranking of each NFT within a collection. Rarity ranking is a proxy

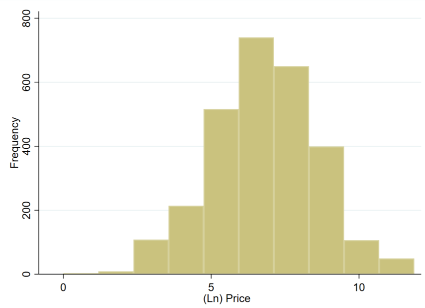
[4] A wash trade is defined as fake and misleading trades typically done to create a false impression of demand and manipulate market prices.




(a)




(b)




(c)

**Figure 2 Distribution of Sales, Revenue, and Price Across Collections**

of the uniqueness of the NFT within a specific collection. It is determined using the metadata associated with an NFT, which provides a list of its features compared to other NFT(s) within the collection. Using rarity ranks of NFT(s) within a collection, we classify the NFT(s) in a collection into categories of Top 20 and Bottom 80 based on the long tail literature (reference XXX). Similarly, we also assess the heterogeneous impact of BNPL on the NFTs in a collection based on the value of the NFT in the pre-treatment period.

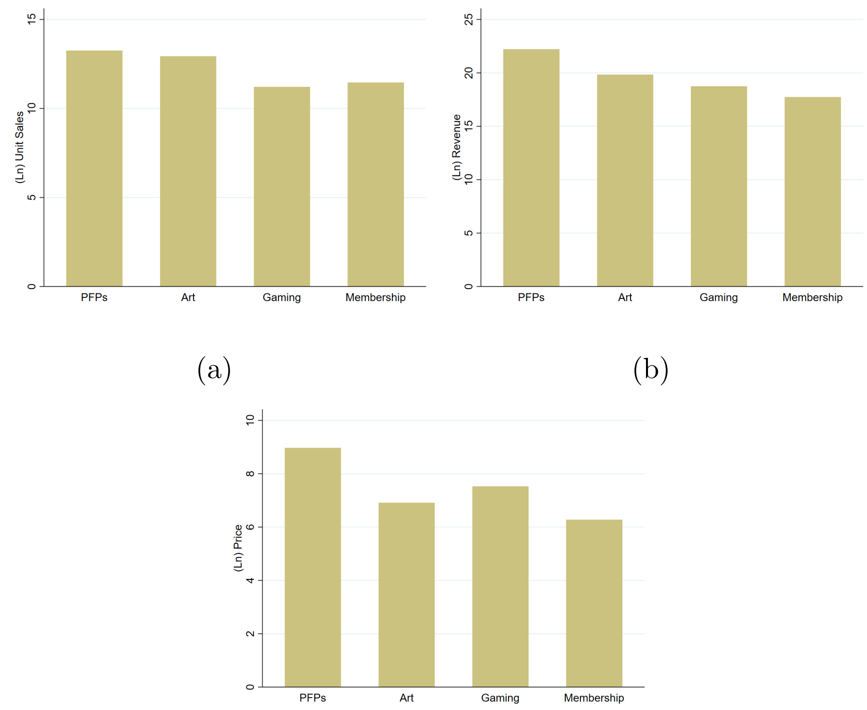
Variables like unit sales, revenue, prices, and listing exhibit significant variability. For instance, some collections may have only a few sales and low revenue in a given week, while others may have hundreds of sales and higher revenue. This large variance in variables can lead to skewness in econometric modeling. To address this issue, we follow previous studies such as Ataman et al. (2010) and apply a log transformation to these variables to ensure they approximate a normal distribution. The details of the log-transformed variables used in the analysis and their summary statistics are provided in Tables 2 and 3.

**Table 2 Description and Transformations Applied to the Variables**

| Variable | Description | Transformations |
|---|---|---|
| UnitSales (Blur) | Weekly total number of NFT sales on Blur platform, eliminating the washtrading | $ln(Sales\_Blur + 1)$ |
| UnitSales (Opensea) | Weekly total number of NFT sales on Opensea platform, eliminating the washtrading | $ln(Sales\_Opensea + 1)$ |
| Revenue (Blur) | Weekly revenue generated from NFT sales by the collection on Blur platform | $ln(Revenue\_Blur + 1)$ |
| Revenue (Opensea) | Weekly revenue generated from NFT sales by the collection on Opensea platform | $ln(Revenue\_Opensea + 1)$ |
| SalePrice (Blur) | Weekly average price of NFT sales by collection on Blur platform | $ln(Price\_Blur + 1)$ |
| SalePrice (Opensea) | Weekly average price of NFT sales by collection on Opensea platform | $ln(Price\_Opensea + 1)$ |
| ActiveUsers (Blur) | Active addresses trading on Blur platform | $ln(ActiveUsers\_Blur + 1)$ |
| ActiveUsers (Opensea) | Active addresses trading on Opensea platform | $ln(ActiveUsers\_Opensea + 1)$ |
| NewUsers (Blur) | Number of users transacting with a collection for the first time on Blur platform | $ln(NewUsers\_Blur + 1)$ |
| NewUsers (Opensea) | Number of users transacting with a collection for the first time on Opensea platform | $ln(NewUsers\_Opensea + 1)$ |
| Listings (Blur) | Total weekly listings of collections on Blur platform | $ln(Listing\_Blur + 1)$ |
| Listings (Opensea) | Total weekly listings of collections on Opensea platform | $ln(Listing\_Opensea + 1)$ |
| Multihome | Total sales on Blur platform relative to the total sales on Opensea and Blur | $ln(MHSales + 1)$ |
| BNPL | Dummy which takes the value 1 for the week when BNPL was introduced by the collection, 0 otherwise. | |

**Table 3 Summary Statistics**

| | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| UnitSales (Blur) | 3.74 | 2.02 | 0 | 9 | 2,499 |
| UnitSales (Opensea) | 3.54 | 1.17 | 0 | 9 | 2,499 |
| Revenue (Blur) | 9.98 | 4.20 | 0 | 18 | 2,499 |
| Revenue (Opensea) | 10.33 | 2.63 | 0 | 16 | 2,499 |
| SalePrice (Blur) | 6.31 | 2.46 | 0 | 12 | 2,499 |
| SalePrice (Opensea) | 6.85 | 1.95 | 0 | 12 | 2,499 |
| ActiveUsers (Blur) | 3.12 | 1.67 | 0 | 8 | 2,499 |
| ActiveUsers (Opensea) | 3.16 | 1.08 | 0 | 8 | 2,499 |
| NewUsers (Blur) | 2.50 | 1.56 | 0 | 7 | 2,499 |
| NewUsers (Opensea) | 2.62 | 1.13 | 0 | 8 | 2,499 |
| Multihome | 0.33 | 0.17 | 0 | 1 | 2,499 |
| Listings (Blur) | 5.07 | 2.39 | 0 | 10 | 2,397 |
| Listings (Opensea) | 5.81 | 1.61 | 0 | 10 | 2,397 |




(c)

**Figure 3 Distribution of sales, revenue, and price across categories**

### 6.1. Model

Our objective is to determine the impact of BNPL, introduced by Blur, on the performance of the NFT collections and the underlying mechanisms. We consider the enabling of the BNPL scheme by Blur as an event and analyze the impact of such events on the sales and revenue of the NFT collections. In our data, the treatment for different collections happened in a staggered manner, i.e., BNPL was announced for different collections occurring at different points in time.

A collection's performance, i.e., sales, revenue, prices, etc., may be impacted by several factors, such as collection owners' social status, collection theme, etc. It is likely that Blur's choice of collections for the policy is also driven by such characteristics. Such omitted variables can be either time-invariant or may vary with time. To address the challenge of obtaining and controlling for all the potential collection characteristics that may be correlated with performance, we incorporate collection fixed effects, specifically to account for time-invariant collection characteristics. This approach is similar to that used in studies such as Kawaguchi et al. (2019) and helps to mitigate the bias due to omitted variables that are time-invariant. Similarly, to account for the time-specific unobserved shocks that may impact the performance of the NFT collections, we incorporate time-fixed effects in our model. Finally, we follow econometric approaches, like Staggered DiD and Synthetic DiD, to address other econometric challenges, such as time-varying unobservables, which are discussed in the subsequent subsections.

**6.1.1. Empirical Approach:** We use the following approaches to assess the impact of Blur's BNPL policy on the performance of the collections: (i) Difference in Difference, (ii) Staggered Difference in Difference, proposed by Gardner (2022), (iii) Synthetic Difference in Difference approach proposed by Arkhangelsky et al. (2021).

**Standard DiD:** Difference-in-difference also referred to as two-way fixed-effects (TWFE) in the context of multiple groups and time periods, is employed to estimate the causal effects of treatments. The underlying assumption is based on the parallel trends assumption, i.e., without the treatment or the policy, treated units would be identical to the untreated units. Moreover, the design also relies on settings with no anticipation effect, i.e., the treatment is not anticipated before adoption, in which case it may affect the pre-treatment behavior of the users. We test for the parallel trends assumption and provide the details in the robustness section. Moreover, Blur made no announcements before the treatment, i.e. introduction of BNPL; therefore, the treatment is likely to be unanticipated for the users. under the above-mentioned conditions, parallel trends and no anticipatory effect, time-varying unobservables, if any, are accounted for by the control group, thereby providing unbiased estimates. To estimate the discussed TWFE model, we use the following specification:

$$Y_{it} = \beta_0 + \beta_1 Treatment_i * Post_{it} + \gamma_i + \eta_t + \epsilon_{it} \tag{1}$$

where $Y_{it}$ is the outcome variable of interest, which is the collection's sales and revenue, $i$ represents the individual collections, and $t$ denotes time. $\gamma_i$ represents time-invariant collection characteristics, $\eta_t$ is unobserved shocks in a given time period that impact all collections, and $\epsilon_{it}$

represents the error term. The error term may be correlated for collection in different time periods and for collections at the same time; thus, to account for such correlations, we cluster the standard error by collection and time.

Athey and Imbens (2022) state that if the treatment timing is random, the standard difference-in-differences (DiD) estimator can be viewed as the weighted average of the average causal effects of changes in the treatment date. Thus, under the condition of random adoption timing, the standard DiD estimator is likely to be unbiased, and its estimates should be statistically similar to Staggered and Synthetic DiD estimators. In the following subsections, we provide an overview of the additional methods we use in our analysis to show robustness and discuss how these methods may address empirical concerns in our analysis.

**Staggered DiD:** Standard Difference in Difference estimation enables us to estimate the impact of the policy on the treated group as compared to the control group that did not receive the treatment. However, as the treatment in our setting is rolled out in a staggered manner, that estimation needs careful consideration to avoid forbidden comparison (Arkhangelsky et al. 2021). Staggered DiD (Gardner 2022) enables us to address the challenge due to staggered adoption, if any, as it involves computing the treatment effects for each cohort separately and finally aggregating them to average effect on the treated. Moreover, it addresses the negative weighting of treatment effects, which may possibly lead to biased estimates (Goodman-Bacon 2018). The approach relies on the parallel trend assumption (shown in robustness section xxx).

To estimate our Staggered DiD model, we follow the approach proposed by Gardner (2022), which involves multiple collections treated at different points in time. In estimating Staggered adoption, one major concern is the estimation biases resulting from heterogeneous treatment effects across groups and periods. Such challenges are addressed in the approach proposed by Gardner (2022). Moreover, this approach retains the efficiency advantages pointed out by Borusyak, Jaravel, and Spiess (2024). The estimation follows a two-step process. In the first stage, the approach makes use of the subsample of untreated/not-yet-treated observations retaining the estimated group and time effects to form the adjusted outcome variable. The first stage is estimated as follows:

$$Y_{igt} = \mu_g + \eta_t + \epsilon_{igt} \tag{2}$$

where $Y_{igt}$ is the outcome variable of interest, which is the collection's sales and revenue, $i$ represents the individual collections, $t$ denotes time, and $g$ stands for group membership where a group is represented by all collections whose treatment begins at time $g$. $\mu_g$ represents time-invariant group characteristics, and $\eta_t$ is unobserved shocks in a given time period that impacts all collections. The adjusted outcomes $\hat{Y_{igt}}$ are then regressed on treatment status in the full sample to estimate treatment effects, as shown in the equation below.

$$\hat{Y_{it}} = \beta_0 + \beta_1 Treatment_i * Post_{it} + \epsilon_{it} \tag{3}$$

**Synthetic DiD:** A significant challenge for identification is the lack of counterfactuals; it is not feasible to observe a collection's performance with and without treatment in the same time period (Wooldridge 2010). Without the ability to compare the outcomes with and without treatment for the same group, it becomes challenging to isolate the true effect of the treatment. In order to address this challenge, the Synthetic DiD constructs a convex combination of control units that closely resembles the treated units, offering a near approximation of the counterfactual outcomes for the unit being predicted (Arkhangelsky et al. 2021).

Arkhangelsky et al. (2021) proposed Synthetic DiD approach overcomes the challenges posed by the traditional synthetic control analysis (as discussed in Abadie et al. 2010), which restricts the sample to having a limited number of treated units in the data. The approach constructs the control group through matching and calculating reweights to ensure that it is identical to that of the treated group.

Finally, Synthetic DiD (Arkhangelsky et al. 2021) enables us to address the challenge due to staggered adoption, if any, as it involves computing the treatment effects for each cohort separately and finally aggregating them to average effect on the treated. It also addresses the negative weighting of treatment effects, which may possibly lead to biased estimates (Goodman-Bacon 2018). In addition to addressing the negative weighting of treatment effects, Synthetic DiD estimates are unbiased even if there is a potential of unobservables correlated with the outcome variable and the treatment, i.e., the choice of collection and the timing of treatment.

In order to implement Synthetic DiD, we create a balanced panel, which is an essential requirement for the algorithm. Following this, we calculate the weights $\hat{\omega}$ based on the pre-treatment trends of the performance variable for both the treated and control units.

Let $N_{control}$ represent the collections in the control group, and $N_{tr}$ stand for the collections in the treated group, and $T = 1, \ldots, T_{pre}$ represent the pre-treatment period. The unit weights are computed as follows:

$$(\hat{\omega_0}\ \hat{\omega_i}) = argmin_{\omega_0 \in \mathbf{R}\ \ \omega_i \in \Omega}\{\sum_{t=1}^{T_{pre}}(\omega_0 + (\sum_{i \in N_{control}} \omega_i Y_{it} - \frac{1}{N_{tr}} \sum_{i \in N_{tr}} Y_{it})^2 + \zeta T_{pre}||\omega||_2^2\} \tag{4}$$

where $\hat{\omega_0}$ denotes the intercept and $\hat{\omega_i}$ are the weights assigned to the collection $i$. $\zeta$ stands for the regularization parameter in order to lower the variance and to assure the uniqueness of the weights. $Y_{it}$ stands for our dependent variable of interest, i.e., the performance of the NFT collections measured by weekly sales or revenue. In addition to assigning weights to the collections to ensure that the treatment units are comparable to the control units, the method also ensures a constant difference between the average post-treatment outcomes and weighted pre-treatment outcomes of the control unit by incorporating time weights $\lambda_t$. The time weights are created using the pre-treatment time periods similar to the treatment periods for the control group as follows:

$$(\hat{\lambda_0}\ \hat{\lambda_i}) = argmin_{\lambda_0 \in \mathbf{R}\ \ \lambda_i \in \Lambda}\{\sum_{i \in N_{control}}(\omega_0 + (\sum_{t \in T_{pre}} \omega_i Y_{it} - \frac{1}{T_{post}} \sum_{t \in T_{post}} Y_{it})^2\} \tag{5}$$

where $\hat{\lambda_0}$ denotes the intercept and $\hat{\lambda_t}$ are the weights for time $t$. Using the collection and time weights, the estimates for Synthetic DiD is then obtained by optimizing the following:

$$(\hat{\phi}\ \hat{\mu}\ \hat{\alpha}\ \hat{\beta}) = argmin_{\phi,\mu,\alpha,\beta}\sum_{i=1}^{N}\sum_{t=1}^{T}(Y_{it} - \mu - \phi Treatment_{it} - \alpha_i - \beta_t)^2 \hat{\omega}_i \hat{\lambda_t} \tag{6}$$

where $\phi$ represents the average Treatment effect of BNPL on the performance of the NFT collections. $\alpha_i$ and $\beta_t$ represents collection and time fixed effects, respectively. The unit and time weights are represented by $\hat{\omega}_i$ and $\hat{\lambda}_t$, respectively. $\hat{\omega}_i$, created by matching and reweighting the collections in the control group, ensures that these units are similar to the treated units. $\hat{\lambda}_t$ created by matching and reweighting in the time dimension, ensures that pre-treatment period is similar to that of treatment times. These weights account for any bias arising due to unobservables and eliminate the requirement of parallel trends. The estimates using the two discussed approaches, i.e., Staggered and Synthetic DiD, are presented in the following subsections.

## 7. Results

**Model Free Evidence:** In order to create the model-free plots to visualize the difference in the unit sales and revenue before and after BNPL was enabled, we create a stacked set, using a time window of 40 weeks before and after the introduction of BNPL. Each panel stack includes the collections that were treated in that cohort (i.e., week), as well as collections that were never treated. We stack the panel datasets created around each collection treatment week, similar to the stacked DID approach. In Figure 4, we present plots showing average unit sales for the treated and the control collections during the time window.

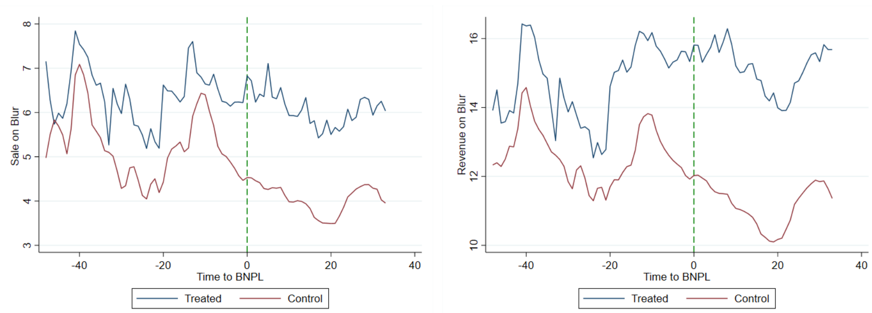



**Figure 4 Model Free Plots for Unit Sales and Revenue for the Control Group and the Treatment**

The red line shows the trend for the control group, while the blue one represents the trend for the treatment group. The plots are suggestive of an increased difference between the unit sales and revenue of the treatment and the control group after the treatment was given. However, these results are subject to potential confounding variables that may influence unit sales and revenue.

Therefore, we estimate our empirical model to account for these factors and present the results from our model estimation.

**Main Effects**: Using the Standard, Staggered, and Synthetic DiD models discussed in the previous section, we analyze the impact of BNPL on the performance of the collections, on Blur and Opensea, measured by weekly unit sales, prices, and revenue. Traditional and Staggered DiD method relies on parallel trend assumption between the control and the treatment groups, which we test using the Wald test for parallel trends. With a $p$-value of .13, we were able to validate the parallel trend assumption to confirm the applicability of Staggered DiD in our context. The estimates for our main model are shown in Tables 4-9, wherein we control for collection-fixed effects and week-fixed effects.

Tables 4 and 5 present the estimates of BNPL on the unit sales of the treated collections on Blur and Opensea. Specification 1 of Table 4 presents the estimation coefficient using standard DiD, which suggests that BNPL-enabled collections witnessed a positive and significant increase in the unit sales post-treatment ($\beta : .528$), valued at approximately .69 units (calculated as $e^{.528} - 1$).The coefficients from Staggered and Synthetic DiD estimation, as shown in specifications 2 and 3 of Table 4, are positive and significant, estimated at .522 and .398, respectively. It is important to note that there is no statistical difference between the estimates obtained from the Standard, Staggered, and Synthetic DiD (as shown in specifications 1, 2, and 3 of Table 4, respectively), suggesting that the estimates obtained from standard DiD are unbiased, thereby, highlighting that our treatment can be treated as random one (Athey and Imbens 2022).

**Table 4** **Impact of BNPL on Unit Sales of Collections on Blur**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| UnitSales | $0.528^{**}$ | $0.522^{**}$ | $0.398^{**}$ |
| | (0.249) | (0.218) | (0.187) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 5 Impact of BNPL on Unit Sales of Collections on Opensea**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| UnitSales | 0.067 | 0.045 | 0.036 |
| | (0.159) | (0.137) | (0.167) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 5 shows the effect of BNPL (offered on Blur) on the sales of BNPL-enabled collections on Opensea. The estimates obtained from Standard, Staggered, and Synthetic DiD (.067, .045, .036, respectively) are insignificant, suggesting that while these collections enjoy an increase in unit sales on Blur, their sales on Opensea remain unaffected. With the increase in sales of the BNPL-enabled collections on Blur, it is likely that the prices of the NFT(s) in these collections are also impacted, particularly due to the increased cash flow among the NFT traders enabled by the BNPL strategy. Therefore, we estimate the impact of BNPL on the sale price of the NFT(s) in the treated collections and present the results in Tables 6 and 7.

**Table 6 Impact of BNPL on Unit Prices of Collections on Blur**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| SalePrice | 0.117 | 0.206 | -0.097 |
| | (0.234) | (0.220) | (0.163) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 7 Impact of BNPL on Unit Prices of Collections on Opensea**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| SalePrice | 0.182 | 0.225 | -0.030 |
| | (0.408) | (0.219) | (0.152) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

The estimates in Specifications 1, 2, and 3 of Table 6, obtained through the Standard, Staggered, and Synthetic DiD, indicate that there is no significant impact of BNPL on the NFT prices of the treated collections. While the unit sales of the NFTs in the treated collections increase (as shown in Table 4), interestingly, there is no impact on the prices of the NFTs being sold. Similar to Blur, the impact of BNPL on the treated collections on Opensea, as shown by the estimates of $SalePrice$ in Specifications 1, 2, and 3 of Table 7, are insignificant.

We, finally, examine the impact of BNPL on the weekly USD sales of the treated collections on Blur and Opensea and present the estimates in Tables 8 and 9 for Blur and Opensea, respectively. The USD sales of the treated collections on Blur increase significantly (as shown by the coefficients of $Revenue$ in Specifications 1, 2, and 3 of Table 8). For Opensea, the estimates obtained from Standard and Staggered DiD are marginally positive and significant (as shown in Specifications 1 and 2 of Table 9), while the Synthetic DiD estimates are insignificant (as shown in Specifications 3 of Table 9). Thus, underscoring that on Opensea, the weekly USD sales of these collections are largely unaffected.

Together, the estimates in Tables 4-6 suggest that Blur's initiative of introducing financial flexibility for NFT collections led to higher unit sales and thereby increased revenue from this collection. Surprisingly, the gains were limited to the Blur platform, where the treatment was available, with a spillover effect on the competing Opensea platform, where these collections were also traded.

A concern that may arise is that there could be collection-related time-varying unobservables that may be driving the positive effect on the sales and revenue of the BNPL-enabled collections on Blur. However, if that argument is true, we should also see a similar effect of these collections on Opensea, the lack of which enables us to rule out the possibility that collection-related time-varying unobservables, correlated with treatment, are a source of bias in our study. Moreover, in the above analyses, it is worthwhile to note that the estimates from Standard DiD are statistically similar to Synthetic DiD, whose estimations are based upon a matched sample and account for unobservables; this further helps us argue that our setting is likely to be unbiased of endogeneity concerns.

**Table 8 Impact of BNPL on Revenue of Collections on Blur**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| Revenue | $1.217^{**}$ | $1.178^{***}$ | $1.399^{**}$ |
| | (0.491) | (0.417) | (0.574) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 9 Impact of BNPL on Revenue of Collections on Opensea**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| Revenue | $0.567^{*}$ | $0.523^{*}$ | 0.446 |
| | (0.334) | (0.309) | (0.501) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

### 7.1. Heterogeneity and Mechanisms

An NFT collection consists of several NFTs, i.e., on average, the size of the NFT collection may vary from 10 to 20000. The individual NFTs within a collection may significantly differ from each other in terms of their valuation and rarity. In the subsequent subsections, we analyze the differential impact of BNPL on different NFTs within a collection, along with other underlying mechanisms that may explain the increased unit sales and the revenue generated by the treated collections on Blur. Drawing from the existing literature, below we provide a discussion on the plausible explanation and the associated analysis for the increase in the transactions and revenue, as shown in Tables 4 and 8. Specifically, we discuss the role of the advertisement effect (Cite XXX), Competition effect (Cite XXX), Income effect (Cite XXX), NFT Heterogeneity, and the Supply side changes in increasing sales and revenue of BNPL-enabled collections on Blur.

**Advertisement Effect:** Typically, the introduction of BNPL is accompanied by Blur making the announcement on X (previously known as Twitter) and other social media platforms. Such announcements may attract users' attention to the treated collections, as shown in prior studies such as XXX, which may subsequently affect their sales and revenue. If the advertisement effect were at play, we would expect a positive effect on the sales of BNPL-enabled collections both on Blur and for the transactions in Opensea. However, the increase in transactions is only limited to the BNPL-enabled collections on Blur (as shown in Tables XXX). This helps us rule out the role of the advertisement effect in increased sales and revenue of the treated collections on Blur.

If the advertisement effect were a dominant factor for the treated collections, we should also expect a greater number of new users engaging with the collections (Cite XXX). Thus, we estimate the impact of BNPL on the new users engaging with the treated collections on Blur and Opensea and present the results in Tables 10 and 11, respectively. The estimates in Tables 10 and 11 for $NewUsers$ (obtained through Standard, Staggered, and Synthetic DiD) are insignificant, indicating that the introduction of BNPL does not bring in new users to Blur or Opensea or result in market expansion. Thus, we can rule out the effect of Advertisement in increased sales and revenue of BNPL collections on Blur.

**Table 10 Impact of BNPL on New Users on Blur**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| NewUsers | 0.208 | 0.213 | -0.006 |
| | (0.182) | (0.163) | (0.153) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 11 Impact of BNPL on New Users on Opensea**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| NewUsers | 0.106 | 0.085 | -0.057 |
| | (0.132) | (0.123) | (0.144) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Income Effect:** The availability of an additional source of income to support the transactions on Blur's BNPL-enabled transaction may plausibly lead to increased sales and revenue. To explore the role of this mechanism in explaining the increased unit sales and revenue of the BNPL enables collections on Blur, we assess the following measures: (i) First, following the prior literature (cite XXX), we estimate the impact of BNPL on user engagement, measured by the number of active users, (ii) Second, we categorize the NFT(s), within a collection, based on their prices (before BNPL was enabled) and rarity, into Top 20 and Bottom 80 (based on the 20-80 long tail rule), to assess whether with the increased cash flow whether users buy more quantity or more in terms of quality, i.e., expensive/ rare NFTs. Provide motivation and cite XXX.

The estimates for the impact of BNPL on user engagement, measured by the number of active users on Blur and Opensea, are presented in Tables 12 and 13, respectively. The estimates of $ActiveUsers$ in Table 12, obtained through Standard, Staggered, and Synthetic DiD, are positive and significant, suggesting that offering BNPL increases users' engagement on the treated collections in Blur. Since there is no increase in the number of new users on Blur (as shown in Table 10), it is reasonable to state that the higher engagement is due to the increased income of the existing users on Blur. While we find an increase in users' engagement on the treated collections in Blur, such effects are absent on opensea, as shown by the insignificant coefficients of $ActiveUsers$ in Table 13.

**Table 12 Impact of BNPL on Active Users on Blur**

| | (1)<br>DiD | (2)<br>Staggered DiD | (3)<br>Synthetic DiD |
|---|---|---|---|
| ActiveUsers | $0.455^{***}$ | $0.446^{***}$ | $0.330^{**}$ |
| | (0.158) | (0.165) | (0.153) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Overall, the findings suggest that the increased unit sales and revenue of treated collections in Blur are likely due to increased engagement or transactions from the existing users due to increased credit opportunities. Consistent with the insignificant impact of introducing BNPL by Blur on Opensea's treated collections' sales and revenue, there is no significant impact on user engagement either.

**Table 13 Impact of BNPL on Active Users on Opensea**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| ActiveUsers | 0.086 | 0.066 | -0.023 |
| | (0.147) | (0.116) | (0.142) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

In addition to the engagement of active users, we also examine the heterogeneous effects of increased availability of credit for expensive and rare NFT(s) are presented in Tables 14 and 15, respectively. The estimates in Table 14 and 15 suggest that BNPL results in the increased sales of expensive/rare NFT(s) on Blur (as shown by the coefficient of $Top20XBlur$ in Specification 1), while the effect on these NFTs on Opensea is insignificant or marginally significant (as shown by the coefficient of $Top20XOS$ in Specification 1). Further, the effect on the less expensive NFTs of the treated collections on Opensea and Blur is insignificant and marginally significant (as shown by the coefficient of $Bottom80XOpensea$ and $Bottom80XBlur$ in Specification 1), respectively. This suggests that users are using the additional income source for more expensive/rare NFTs on Blur.

**Table 14 Heterogeneity Effect by Price**

| | (1) Sales | (2) Price |
|---|---|---|
| Top20 X OS | 0.178 | -0.424 |
| | (0.307) | (0.279) |
| Top20 X Blur | 1.541$^{***}$ | -0.121 |
| | (0.383) | (0.217) |
| Bottom80 X OS | -0.093 | 0.099 |
| | (0.189) | (0.218) |
| Bottom80 X Blur | 0.429$^{*}$ | 0.124 |
| | (0.219) | (0.215) |
| Constant | 3.547$^{***}$ | 7.286$^{***}$ |
| | (0.050) | (0.059) |
| Observations | 9594 | 9594 |

Clustered Standard errors in parentheses.

**Table 15 Heterogeneity Effect by Rarity**

| | (1) Sales | (2) Price |
|---|---|---|
| Top20 X OS | 0.347* | 0.165 |
| | (0.180) | (0.196) |
| Top20 X Blur | 0.689*** | 0.170 |
| | (0.186) | (0.200) |
| Bottom80 X OS | 0.186 | 0.183 |
| | (0.162) | (0.206) |
| Bottom80 X Blur | 0.355* | 0.163 |
| | (0.211) | (0.204) |
| Constant | 3.437*** | 7.185*** |
| | (0.049) | (0.052) |
| Observations | 9560 | 9560 |

Clustered Standard errors in parentheses.

The impact on price is shown in Specification 2 of tables Tables 14 and 15 to find that the prices of the different NFTs remain unaffected. Overall, these estimates underscore that users supplement their existing funds using BNPL income for the rare/expensive NFTs, increasing their sales. However, user engagement with less expensive and rare NFTs with BNPL available funds remains insignificant. To summarize, the estimates presented in Tables 12-15 suggest that the introduction of BNPL results in increased activity of the existing users, wherein these users engage with the expensive/rare NFTs due to the increased income effect.

**Competition effect:** The availability of BNPL on Blur (and lack of it on Opensea) may impact the competitive dynamics by affecting users' multihoming or switching tendencies between the two competing platforms. While users' switching tendencies can be ruled out due to the insignificant impact of BNPL on the active users of Opensea (Table 13), we test this mechanism by assessing the impact of BNPL on users' multihoming behavior; the estimates using Standard, Staggered, and Synthetic DiD are presented in 16. The independent variable *Multihome* is defined as the share of weekly transactions by a user on Blur, divided by the total number of transactions (i.e., on Blur and Opensea); we then aggregate this measure across all the users in a given week. We find that the introduction of BNPL increases the pie of BLur in users' portfolios, highlighting the implications of the policy in providing a competitive edge to Blur against a large incumbent platform, i.e., Opensea.

**Table 16 Impact of BNPL on Users Multi-homing Behaviour**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| Multihome | 0.074*** | 0.073*** | 0.068*** |
| | (0.019) | (0.019) | (0.018) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Supply Side change:** In addition to the mechanisms driven by buying behavior, the introduction of BNPL may also impact the availability of NFTs for sale, which may subsequently result in increased unit sales and revenue of the treated collections. In order to test this mechanism, we assess the impact of BNPL on the NFT listings on Blur and Opensea; the estimates, using Standard, Staggered, and Synthetic DiD, for Blur and Opensea are presented in Tables 17 and 18, respectively. The estimates of Listings Table 17 are positive and significant, suggesting that the availability of BNPL encourages the NFT owners to list their NFT more on Blur, impacting the availability of NFT tokens. However, the effect on the listings on Opensea is insignificant, as shown in Table 17

As the increase in unit sales is primarily from the expensive NFTs, we next assess the BNPL's impact on listings for different NFT types on Blur and Opensea. The estimates are presented in Table 19. We find that listings for both Top20 and Bottom80 NFTs of the treated collected increase (as shown by the coefficients of $Top20XBlur$ and $Bottom80XBlur$). If increased listing were to be the underlying mechanism for increasing unit sales and revenue of the treated collection, then we should expect higher sales for NFT(s) in the Top 20 and Bottom 80 segments, as both these types experience an increase in listings. However, the increased sales are limited to rare/ expensive NFT(s). Thus, we can rule out the increased availability of NFTs as the underlying mechanism explaining increased unit sales and revenue due to BNPL.

**Table 17 Impact of BNPL on Listings of Collections on Blur**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| Listings | 0.785*** | 0.753*** | 0.758* |
| | (0.252) | (0.232) | (0.445) |
| Observations | 2397 | 2397 | 2397 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 18 Impact of BNPL on Listings of Collections on Opensea**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| Listings | 0.764 | 0.679 | 1.225 |
| | (0.638) | (0.571) | (0.765) |
| Observations | 2397 | 2397 | 2397 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 19 Heterogeneity effect on Listings by price.**

| | (1) Listing |
|---|---|
| Top20 X Blur | 1.936*** |
| | (0.287) |
| Top20 X OS | -0.428 |
| | (0.473) |
| Bottom80 X Blur | 2.530*** |
| | (0.432) |
| Bottom80 X OS | 0.261 |
| | (0.591) |
| Constant | 2.477*** |
| | (0.067) |
| Observations | 10406 |

Clustered Standard errors in parentheses.

## 7.2. Robustness

We perform a series of robustness checks to establish the validity of our main results and underlying mechanisms as follows:

**7.2.1. Threats to SUTVA:** The collections for which BNPL was enabled by Blur form our treatment group, whereas collections from other categories such as Gaming, Membership, Art, and untreated top collections of PFPs constitute the control group. It is plausible that the users trading in the treatment collection also engage with the collections in the control group. Table 20 presents the number of overlapping users between the treatment and the control group NFT categories, which varies from 9.6 percent for the Membership category to 26.20 percent for the Art category. In that case, such overlapping users' behavior in the treated collections will also be a part of the transactions in the control group. Thus, any change in their behavior due to BNPL introduced in the treatment group may spill over to their actions in the control collections they engage in; this plausible interference could perhaps be a threat to SUTVA.

**Table 20 Users Overlap Between Collections/ Categories**

| Category | User | Overlapping | BNPLUsers | Overlapping(percent) |
|---|---|---|---|---|
| Gaming | 15409 | 6624 | 49948 | 13.2 |
| Membership | 18118 | 4820 | 49948 | 9.6 |
| Art | 42368 | 13089 | 49948 | 26.20 |
| Meebits–Doodles | 9917 | 5817 | 49948 | 11.64 |

To address this issue, we use the following approaches: (i) Eliminate overlapping users, both in the treatment and the control group (XXX), (ii) Analysis with a subset of control collections with minimal overlap in users between the treated collections (XXX), (iii) An alternate model specification that accounts for the overlap. If substitution or complementary spillover effects are at play, they are likely to be more pronounced for the collections in the control group having a higher number of shared users with the treated group (XXX).

**Eliminate Overlapping Users:** We eliminate the overlapping users, both in the treatment and the control group, so as to assess the impact of the BNPL strategy using only the behavior of the users exclusive to the treatment and the control group.

Eliminating the transactions from the overlapping users, we present the estimates for unit sales for Blur and Opensea in Tables 21, 22, respectively. Additionally, we present the analysis for prices and revenue in the Appendix in Tables EC.1, EC.2, EC.3 and EC.4, respectively. Consistent with our main analyses (as shown in Tables 4 and 5), the estimates in Tables 21, 22 show that treated collections witness an increase in unit sales, while there is an insignificant on the collections unit sales on Opensea. Similarly, the estimates of $SalePrice$, presented in Tables EC.1, and EC.2, are insignificant for both Blur and Opensea (consistent with our main estimates shown in Tables 6 and 7). Finally, the estimates of *Revenue* after eliminating the overlapping users are shown in Tables EC.3 and EC.4, are also consistent with our main findings showing an increase in the revenue of the treated collections of Blur, while an insignificant effect on the revenue of the BNPL treated collections on Opensea. Together, these estimates help us establish the robustness of our findings.

**Table 21** **Impact of BNPL on Unit Sales of Collections on Blur Eliminating Overlapping Users**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| UnitSales | $0.489^{***}$ | $0.485^{**}$ | $0.351^{**}$ |
| | (0.184) | (0.222) | (0.169) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 22** **Impact of BNPL on Unit Sales of Collections on Opensea Eliminating Overlapping Users**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| UnitSales | 0.013 | -0.007 | -0.030 |
| | (0.184) | (0.140) | (0.176) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Control Group Collections With Minimum Overlap:** As an alternate approach to ensure that SUTVA is not violated, following prior studies such as XXX, we rerun our analysis with the control group having minimal overlap with the treatment collections. We follow prior studies (XXX) to use the threshold of at most 10 percent overlap. The estimates for unit sales on Blur and Opensea are presented in Tables 23, 24, respectively. The estimates in Tables23, 24 demonstrate that treated collections see a gain in unit sales, whereas there is an insignificant impact on the collections unit sales on Opensea. These estimates are consistent with our major studies, as shown in Tables 4 and 5.

**Table 23 Impact of BNPL on Unit Sales of Collections on Blur**

| | (1) Classic DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| UnitSales | 0.526** | 0.517** | 0.607** |
| | (0.261) | (0.224) | (0.292) |
| Observations | 1326 | 1326 | 1326 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 24 Impact of BNPL on Unit Sales of Collections on Opensea**

| | (1) Classic DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| UnitSales | 0.170 | 0.101 | 0.069 |
| | (0.186) | (0.151) | (0.247) |
| Observations | 1326 | 1326 | 1326 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Falsification Test:** We use falsification tests, employing pseudo treatment indicators and dates, to examine whether the estimated treatment effects are inadvertently capturing spurious correlation, following prior studies such as xxx.

In order to implement pseudo-treatment indicators, we randomly select a control series as treated for each treatment collection and then re-estimate the model, excluding the actually treated series. Given that the pseudo indicator is assigned to the control group, which did not receive the treatment, the estimates, in the absence of spurious correlation, are likely to be insignificant Ghose 2009, Jo et al. 2020. We present the estimates for pseudo-treatment indicators in Table 25, wherein we find that the estimates of treatment on the sales of collections are insignificant.

To implement pseudo-treatment dates, we reassign the treatment date to be 3 weeks before the actual treatment date. As the adjusted treatment variable excludes the actual treatment date, the estimates should be insignificant. Table 26 shows the estimated treatment effects for pseudo-treatment dates. The coefficient of unit sales and sale price for Blur is insignificant, and the same holds for the coefficients of sales and sale price for Opensea. These estimates suggest that the effect of BNPL is not merely an artifact of spurious correlation or model specification.

**Table 25 Falsification Tests Using Pseudo Treatment Indicators**

| | Blur | | Opensea | |
|---|---|---|---|---|
| | (1) UnitSales | (2) SalePrice | (3) UnitSales | (4) SalePrice |
| Treatment | -0.241 | 0.220 | -0.114 | -0.204 |
| | (0.229) | (0.299) | (0.139) | (0.154) |
| Observations | 1836 | 1836 | 1836 | 1836 |
| Collection FE | Yes | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses.
$^{*}$ $p<0.10$, $^{**}$ $p<0.05$, $^{***}$ $p<0.01$

**Table 26 Falsification Tests Using Pseudo Treatment Week**

| | Blur | | Opensea | |
|---|---|---|---|---|
| | (1) UnitSales | (2) SalePrice | (3) UnitSales | (4) SalePrice |
| Treatment | -0.101 | -0.150 | -0.045 | 0.151 |
| | (0.270) | (0.305) | (0.121) | (0.303) |
| Observations | 1836 | 1836 | 1836 | 1836 |
| Collection FE | Yes | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses.
$^{*}$ $p<0.10$, $^{**}$ $p<0.05$, $^{***}$ $p<0.01$

**Subsample estimation for Heterogeneity:** In Table 14, we present the heterogeneous impact of BNPL on the Top20 and Bottom80 NFTs using Standard DiD estimation. For robustness, we estimate the heterogenous impact of BNPL on the Top20 and Bottom80 NFTs using Synthetic DiD using subsamples, as interaction analysis is not feasible. Specification 1 of Table 27 shows the impact of BNPL on the Top20 NFTs of the treated collections on Blur; the estimates are positive and significant, consistent with that of Table 14. Similarly, consistent with Table 14, the estimate for $Bottom80$ on Blur is insignificant, reaffirming that the positive effect on unit sales is driven by the expensive NFTs of the treated collections. Finally, the estimates for $Top20$ and $Bottom80$ NFTs of the BNPL treated collection on Opensea are insignificant (consistent with Table 14).

**Table 27 Impact of BNPL on Top 20 and Bottom 80 NFT Tokens' Sales on Blur and Opensea**

| | Synthetic DiD | | | |
|---|---|---|---|---|
| | Blur | | Opensea | |
| | (1) | (2) | (3) | (4) |
| Top20 | 0.791*** | | 0.154 | |
| | (0.212) | | (0.140) | |
| Bottom80 | | -0.063 | | -0.079 |
| | | (0.227) | | (0.195) |
| Observations | 5100 | 5100 | 5100 | 5100 |
| Collection FE | Yes | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

# 8. Plots

To do:

1. Tests to confirm SUTVA assumptions. -parallel trends (done) and Sensitivity analysis
2. Heterogeneity plots by rarity and prices
3. Control for Overlap

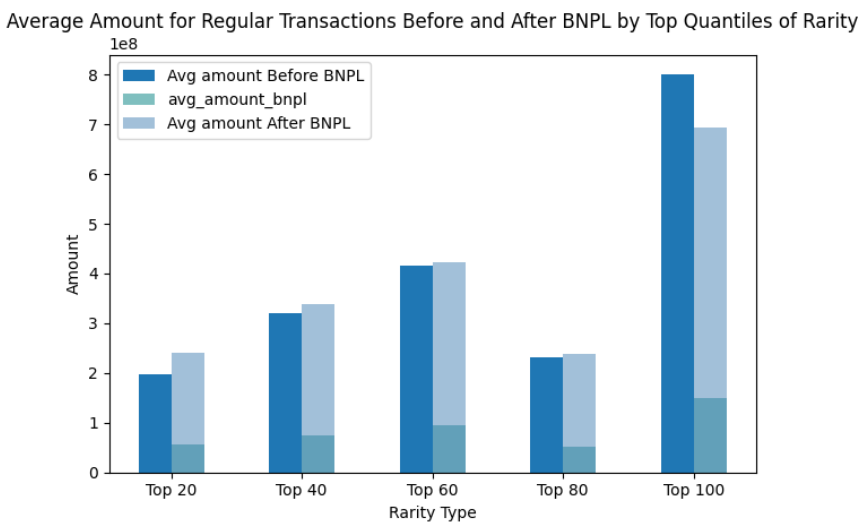



**Figure 5** **Users Spend on Different Rarity Tiers.**

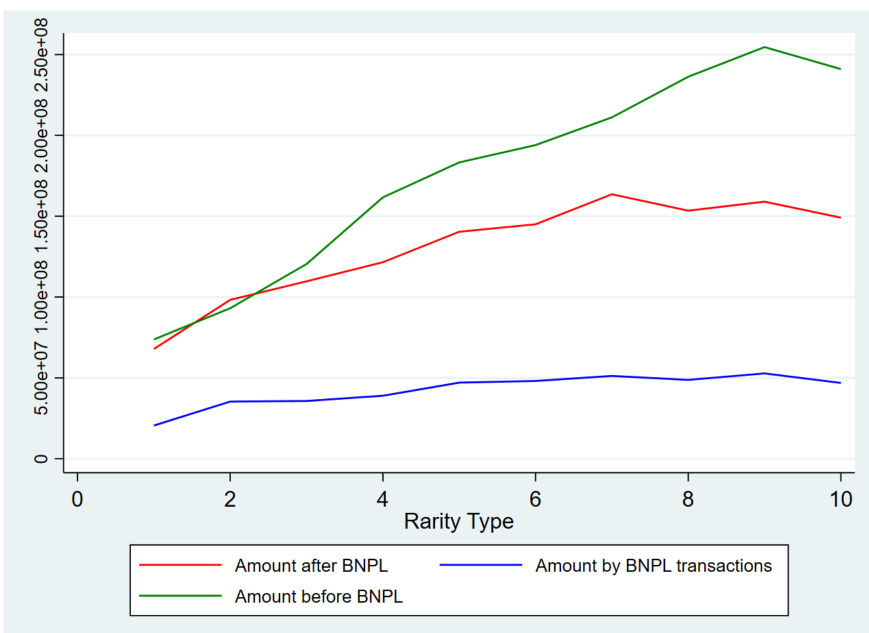



**Figure 6** **Users Spend on Different Rarity Tiers.**

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# E-Companion

**Table EC.1 Impact of BNPL on Unit Prices of Collections on Blur Eliminating Overlapping Users**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| SalePrice | 0.087 | 0.185 | -0.064 |
| | (0.213) | (0.220) | (0.229) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table EC.2 Impact of BNPL on Unit Prices of Collections on Opensea Eliminating Overlapping Users**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| SalePrice | 0.174 | 0.229 | -0.033 |
| | (0.445) | (0.219) | (0.409) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table EC.3 Impact of BNPL on Unit Revenue of Collections on Blur Eliminating Overlapping Users**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| Revenue | $1.217^{**}$ | $1.176^{***}$ | $0.966^{**}$ |
| | (0.508) | (0.403) | (0.403) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table EC.4 Impact of BNPL on Unit Revenue of Collections on Opensea Eliminating Overlapping Users**

| | (1) DiD | (2) Staggered DiD | (3) Synthetic DiD |
|---|---|---|---|
| Revenue | 0.530 | 0.487 | 0.424 |
| | (0.476) | (0.306) | (0.564) |
| Observations | 2499 | 2499 | 2499 |
| Collection FE | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes |

Clustered Standard Errors in Parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$