1. 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. BNPL increases the number of active users, no effect on number of new users, and increases the share of wallet for BLUR.

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.

Positioning: 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.

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.

2. 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.

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

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

3. Data

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].

Starting May 2023, Blur introduced Buy Now, Pay Later (BNPL) feature for few collections in a staggered manner. The strategy 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 up front but still want to invest in these digital assets.

BNPL startegy was enabled for 14 collections selected by BLUR platform belonging to PFP category starting May 2023 in a staggered manner. The collections and the respective timeline of treatment is presented in Table 1. 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.

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. The dark blue area represents treated collection-week observations whereas the light blue area represents the untreated collections in a given week.

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

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

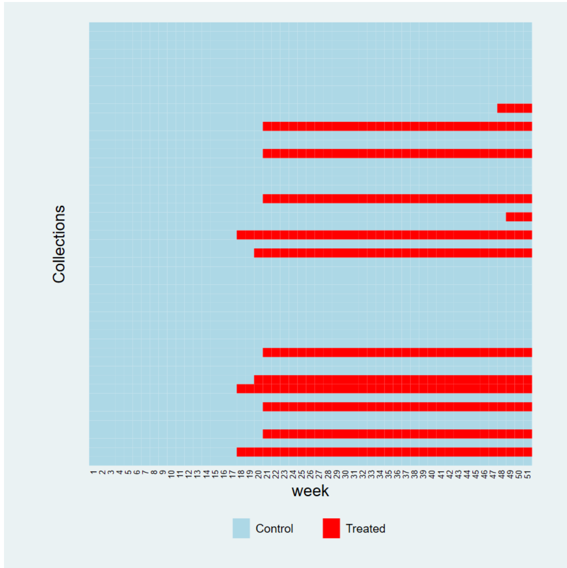

Figure 1 **Treatment Variation Plot.**

Finally, to ensure that there are no spillover from the treatment to control groups, for robustness, we conducted our analysis by identifying and eliminating any overlapping user between the two groups.

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 weekly level for the purpose of our analysis. The transactions 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. The distribution of sale and revenue across categories is shown in Figure 2.

Our data spans January- December 2023 period, i.e., 52 weeks. 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. Additionally, we also capture whether the transaction was seller initiated (i.e., the seller listed the NFT for sale) or buyer initiated (i.e., the seller accepted buyers bid). We also differentiate between a new and existing user, to understand mechanisms related to market expansion and advertisement effect. Finally, we identify whether a sale is a valid one or a wash trade. A wash trade is defined as fake

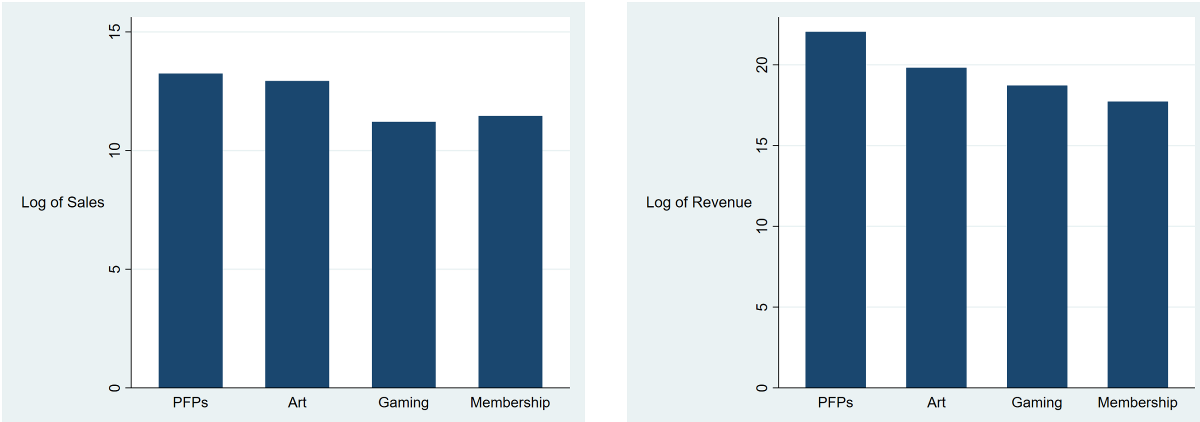

Figure 2 **Distribution sales and revenue across categories.**

and misleading trades typically done to create a false impression of demand and manipulate market prices.

We also examine the differential impact of BNPL on NFT(s) within a collection. For instance, we collected information on the rarity of each NFT. Rarity ranking is a proxy 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 them into categories Top 20 and Bottom 80 based on the long tail literature (reference XXX). Similarly, we also assess the heterogeneous impact of BNPL on collections based on the sales volume and value of the NFT in the pre-treatment period.

We present the summary statistics and the description of the variables in tables 20 and **??** respectively. The unit of data in our analysis is collection, week and platform. Our primary dependent variable, measuring market efficiency, is the number of sales and revenue. Number of weekly sales and weekly revenue presented in the left and right panel of Figure 3 respectively, is seen to be following a log-normal distribution. In addition to number of weekly sales and weekly revenue, to further assess the impact of BNPL on the market efficiency, we compute the average time between two transaction of a given NFT in a collection.

4. Model

Our objective is to determine the impact of BNPL introduced by Blur, on the performance of the NFT collections. We consider the enabling of the BNPL scheme

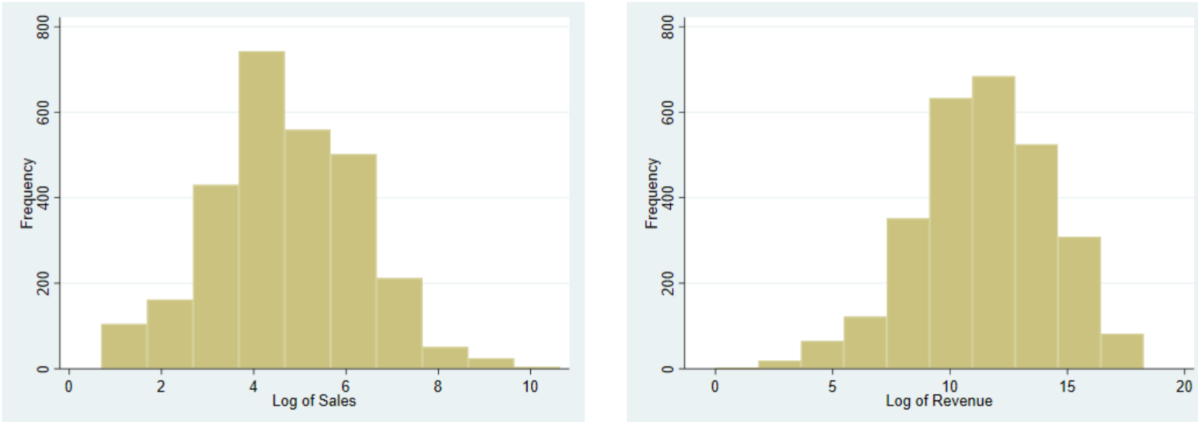

Figure 3 **Distribution sales and revenue.**

by Blur as events 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 occurs at different points in time.

To account for the time-invariant characteristics of a collection, e.g., collection owners' social status, collection theme, etc., that may impact its demand and performance, we include collection fixed-effects. Additionally, to control for the time-specific unobserved shocks that may impact the performance of the NFT collections. Our primary unit of analysis is at weekly level for each collection.

4.1. Empirical Challenges

As the treatment is rolled out in a staggered manner, the estimation needs careful estimation to avoid forbidden comparison (Callaway and Sant'Anna 2021, Arkhangelsky et al. 2021a). Thus, to address the above mentioned challenges we use the following approaches: (i) Classic Difference in Difference (ii) Staggered Difference in Difference, proposed by Butts and Gardner (2021), (iii) Synthetic Difference in Difference approach proposed by Arkhangelsky et al. (2021a),

Both our approach, i.e., Staggered DiD (Callaway and Sant'Anna 2021) and Synthetic DiD (Arkhangelsky et al. 2021a), enable us to address the challenge of staggered adoption, as both these approaches involve computing the treatment effects for each cohort separately and finally aggregating them to average effect on the treated. Both these approaches address negative weighting of treatment effects which may lead to biased estimates **?**. Furthermore, Synthetic DiD estimates are unbiased even if there is a potential of unobservables correlated with the outcome variable and the treatment, i.e., launch of BNPL.

4.1.1. Staggered DiD: Our estimation using the Staggered DiD model proposed by Callaway and Sant'Anna (2021) involves multiple collections treated at different points in time, the unit of analysis being collection and week. Let Y_{it} be the observed outcome variables (e.g., log of the number of weekly sales and log of weekly revenue of a collection), where i represents a collection and t a time period (week). For each collection let R_{ir} be a binary variable equal to 1 if collection i was treated at time r. Finally, let $Y_{it}(0)$ represent collection i's performance at t, if it is untreated at t, and $Y_{it}(r)$ represent collection i's performance at t is the collection i was first treated at time r. Note that once treated, a collection remains treated in our sample. Thus, the collection-week treatment effect can be defined as:

$$ATT(r,t) = E[(Y_{it}(r) - Y_{it}(0)|R_{ir} = 1], \tag{1}$$

where $ATT(r,t)$ captures the average treatment effect at time t for the group of collections for which the time of treatment is r. The framework accounts for heterogenous treatment effects with respect to the timing of the treatment. Note that one of the parallel trend assumptions is critical for the applicability of this approach. We test for the parallel trends assumption in our study and present it in XXX.

4.1.2. Synthetic DiD: Lack of counterfactuals poses a significant challenge for identification, as it is not possible to observe the performance of a collection with and without treatment in the same time period. To overcome this challenge, Synthetic DiD creates a convex combination of the control units that can mimic the treated units, providing a close approximation of counterfactual outcomes of the predicted unit.

Synthetic control analysis **?** requires a small number of treated units. We use the recent adaptation by Arkhangelsky et al. (2021a), which helps overcome this issue. For Synthetic DiD, we construct a balanced panel, wherein first we compute the weights $\hat{\omega}$ using the pre-treatment trends of the performance variable of the treated and the control units. For all $t = 1, ..., T_{pre}$,

$$\hat{\omega}_0 + \sum_{i \in N_{control}} \hat{\omega}_i DV_{it} \approx N_{treat}^{-1} \sum_{i \in N_{treat}} DV_{it} \tag{2}$$

where $\hat{\omega_0}$ denotes the intercept and $\hat{\omega_i}$ are the weights assigned to the collection i. In addition to assigning weights to the collections to ensure that the treatment units are comparable to the control units, the method also ensures constant difference between the average post-treatment outcomes and weighted pre-treatment outcomes of the control unit by incorporating time weights λ_t. The estimate for the Synthetic DiD is obtained by aggregating the following:

$$(\hat{\tau}\ \hat{\mu}\ \hat{\alpha}\ \hat{\beta}) = argmin_{\tau,\mu,\alpha,\beta} \sum_{i=1}^{N} \sum_{t=1}^{T} (DV_{it} - \mu - \alpha_i - \beta_t)\hat{\omega}_i \hat{\lambda_t} \tag{3}$$

5. Analysis

Table 1 provides the 14 collections from the PFP category and the timeline of BNPL availability for these collections on Blur.

Main Effects: Table 2 shows the effect of BNPL on the sales of BNPL-enabled collections on Blur and Opensea. The results show that BNPL results in an increase in the sales and revenue of the BNPL-enabled collections on Blur Platform, however, on average it does not increase the price of NFT(s) sold on Blur. On Opensea, there is no impact on the sales or prices and a marginal positive effect on the revenue of the collections offering BNPL on Blur. Additionally, we find that the time to sale (after being listed) decreases for BNPL collections as shown in Table 3.

Robustness: In addition to classic DID we employ Staggered and Synthetic DID, to ensure our estimates are robust to the model specifications, and heterogeneity in outcomes across collections and over time. We use the top collections from other categories as our control group. One concern may be related to the validity of the control group, as there may be overlapping users transacting in both BNPL-enabled collections and the collections in the control group. To address this concern, we eliminated the overlapping users between the control and the BNPL-enabled collections and estimated the impact of BNPL on the sales, revenue, and prices of the collections on Blur and Opensea based on the exclusive non-overlapping user group. The results are presented in Table 10 and are consistent with our findings presented in Table 2.

Another 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 is a concern in our study.

5.1. Heterogeneity and Mechanisms

The plausible explanation for the increase in the transactions and revenue as shown in Table 2 is as follows:

1. **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. We test this mechanism by assessing the impact of BNPL on the number of active users, and their multihoming behavior. As shown in table 11, BNPL increases the number of active users on Blur's BNPL-enabled collections and the pie of BLUR in users' portfolios, highlighting that this is a potential tool for platforms to shield against multihoming.

2. **Advertisement Effect:** If the Advertisement effect would be at play we should see 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. Moreover, we should see more number of new users, however, in Table 11 we find that 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.

3. **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 this mechanism 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.) The heterogeneous effects for expensive and rare NFT(s) are presented in Tables 13 and 14 respectively. The estimates suggest that BNPL results in the increased sales of expensive and rare NFT(s) on Blur. This suggests that users are using the additional income source for more high-quality products. We plot users' average spend on the NFTs by rarity, before and after BNPL in Figure 4. The figure shows that user spend on more Rare NFT(s) from their own funds remain the same pre and post BNPL scheme. They use the BNPL fund to supplement their income and buy more rare NFT(s). For the less rare NFT(s), users substitute their funds with the BNPL funds.

Overall, the analysis and the figure shows that users supplement their existing funds using BNPL income for the rare/expensive NFT(S) increasing its sales. However, users substitute their funds with BNPL available funds for purchasing the low quality or less rare NFT(s), maintaining the sales volume similar to the pre -BNPL times.Thus, the effect of BNPL is driven by increased income effect.

4. **Supply Side change:** In table 15 we see that as a result of BNPL, NFT owners start to list more. So, BNPL does affect the assortment of NFT tokens. The heterogeneity effect for the expensive and rare NFT(s) are shown in Table 16 and 17 respectively, however, The listing for both the rare (expensive) and other NFT(s) increase on Blur. If increased listing were to increase the sales, then we should expect higher sales for NFT(s) in the Top 20 and Bottom 80 segment, however, the increased sales is limited to rare/ expensive NFT(s).

Moreover, when we control for the number of listings in Table 18, we still find a statistically significant impact of BNPL on Transactions. Moreover, the difference in the coefficient of BNPL in Table 2 and 18 is statistically insignificant. Thus, the increase in sales is not likely to be explained by the change in the assortment or higher liquidity.

Table 1 BNPL enabled collections and control group.

Collection	BNPL Week in 2023
Azuki	18
Beanzofficial	21
Bored-ape-kennel-club	21
Boredapeyachtclub	20
Clonex	21
Kanpai-pandas	21
Degods	19
Milady	18
Mutant-ape-yacht-club	20
Otherdeed	21
Pudgypenguins	21
Remilio-babies	21
Moonbirds	48
Lilpudgys	49
Control Groups	
Top collections of categories- Art, Membership, Gaming	
Meebits, Doodles(Other PFPs)	

Table 2 Impact of BNPL on Sales. The unit of data is collectionid and week.

	(1) #QuantityBlur	(2) #QuantityOS	(3) RevenueBlur	(4) RevenueOS	(5) PriceBlur	(6) PriceOS
DID	0.521**	0.068	1.169***	0.544*	0.212	0.230
	(0.221)	(0.165)	(0.423)	(0.315)	(0.218)	(0.216)
Staggered DID	0.522**	0.045	1.178***	0.523*	0.206	0.225
	(0.219)	(0.139)	(0.419)	(0.312)	(0.220)	(0.219)
Synthetic DID	0.398**	0.036	1.399***	0.446	-0.097	-0.030
	(0.184)	(0.170)	(0.532)	(0.493)	(0.182)	(0.156)
Observations	2499	2499	2499	2499	2499	2499
Collection FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 Impact of BNPL. The unit of data is collectionid and week.

	(1) TimeToSale
DID	-0.245**
	(0.117)
Staggered DID (Butts and Gardner 2021)	-0.263**
	(0.109)
Synthetic DID (Arkhangelsky et al. 2021b)	-0.370***
	(0.089)
Observations	2499
Collection FE	Yes
Week FE	Yes

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 Results of Falsification Tests using Pseudo Treatment Event.

	(1) SalesBlur	(2) SalesOS	(3) RevenueBlur	(4) RevenueOS	(5) PriceBlur	(6) PriceOS
DID	0.313	0.320**	0.597*	0.604***	0.197	0.188
	(0.194)	(0.157)	(0.323)	(0.209)	(0.165)	(0.158)
Staggered DID	0.296*	0.368**	0.550**	0.604***	0.122	0.116
	(0.158)	(0.170)	(0.267)	(0.194)	(0.190)	(0.188)
Observations	2153	2153	2153	2153	2153	2153
Collection FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 Impact of BNPL . The unit of data is collectionid and week.

	(1) lnlistingbysale_blur	(2) lnlistingbysale_OS
DID	-0.239**	0.164
	(0.098)	(0.116)
Staggered DID	-0.245***	0.176
	(0.071)	(0.121)
Synthetic DID	-0.132	0.191*
	(0.090)	(0.102)
Observations	2499	2499
Collection FE	Yes	Yes
Week FE	Yes	Yes

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 Impact of BNPL, when activity is BID . The unit of data is collectionid and week.

	(1) #QuantityBlur	(2) #QuantityOS	(3) RevenueBlur	(4) RevenueOS	(5) PriceBlur	(6) PriceOS
DID	0.471^{**}	0.158	1.038^{**}	0.704^{**}	0.143	0.223
	(0.226)	(0.131)	(0.405)	(0.321)	(0.216)	(0.217)
Staggered DID	0.473^{**}	0.133	1.048^{***}	0.678^{**}	0.135	0.221
	(0.226)	(0.124)	(0.401)	(0.311)	(0.220)	(0.221)
Synthetic DID	0.299	0.047	0.577^{*}	0.290	-0.082	0.038
	(0.270)	(0.144)	(0.333)	(0.252)	(0.218)	(0.143)
Observations	2499	2499	2499	2499	2499	2499
Collection FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Clustered Standard errors by collectionid and week in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 Impact of BNPL, when activity is ASK. The unit of data is collectionid and week.

	(1) #QuantityBlur	(2) #QuantityOS	(3) RevenueBlur	(4) RevenueOS	(5) PriceBlur	(6) PriceOS
DID	0.397^{*}	-0.013	1.061^{**}	0.492	0.142	0.203
	(0.221)	(0.191)	(0.422)	(0.315)	(0.209)	(0.218)
Staggered DID	0.387^{*}	-0.034	1.059^{***}	0.473	0.135	0.196
	(0.212)	(0.150)	(0.404)	(0.310)	(0.213)	(0.221)
Synthetic DID	0.272	-0.097	0.705^{**}	0.489	0.008	-0.106
	(0.234)	(0.178)	(0.340)	(0.533)	(0.198)	(0.210)
Observations	2499	2499	2499	2499	2499	2499
Collection FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Clustered Standard errors by collectionid and week in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 **Interaction analysis on the basis of activity. The unit of data is collectionid, week, and activity.**

	(1) Sales	(2) Price	(3) Revenue
BNPL_Ask_OS	0.105	0.131	0.425
	(0.187)	(0.210)	(0.259)
BNPL_Ask_Blur	0.529^{**}	0.107	0.869^{**}
	(0.208)	(0.200)	(0.354)
BNPL_Bid_OS	0.305^{**}	0.093	0.574^{**}
	(0.144)	(0.206)	(0.285)
BNPL_Bid_Blur	0.378^{*}	0.138	0.727^{*}
	(0.224)	(0.208)	(0.372)
Constant	3.585^{***}	6.956^{***}	10.243^{***}
	(0.044)	(0.048)	(0.091)
Observations	10966	10966	10966

Clustered Standard errors by collectionid and week in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9 **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

Table 10 **Robustness: Impact of BNPL. Eliminating overlapping users. The unit of data is collectionid and week.**

	(1) SalesBlur	(2) SalesOS	(3) RevenueBlur	(4) RevenueOS	(5) PriceBlur	(6) PriceOS
DID	0.485^{**}	0.014	1.164^{***}	0.506	0.192	0.234
	(0.224)	(0.169)	(0.413)	(0.311)	(0.217)	(0.215)
Staggered DID	0.485^{**}	-0.007	1.176^{***}	0.487	0.185	0.229
	(0.222)	(0.142)	(0.406)	(0.308)	(0.220)	(0.219)
Synthetic DID	0.351^{*}	-0.030	0.966^{**}	0.424	-0.064	-0.033
	(0.192)	(0.174)	(0.435)	(0.557)	(0.175)	(0.231)
Observations	2499	2499	2499	2499	2499	2499
Collection FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Clustered Standard errors by collectionid and week in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6. Mechanisms

Table 11 Multihoming. The unit of data is collectionid and week.

	(1) Active_user_B	(2) Active_user_OS	(3) new_user_B	(4) new_user_OS	(5) MHSales	(6) MHAmount
DID	0.440**	0.084	0.214	0.099	0.070***	0.023*
	(0.168)	(0.140)	(0.170)	(0.146)	(0.019)	(0.013)
Staggered DID	0.446***	0.066	0.213	0.085	0.073***	0.022**
	(0.166)	(0.118)	(0.164)	(0.125)	(0.019)	(0.011)
Synthetic DID	0.330**	-0.023	-0.006	-0.057	0.068***	0.026
	(0.140)	(0.145)	(0.181)	(0.143)	(0.022)	(0.018)
Observations	2499	2499	2499	2499	2499	2499
Collection FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12 Heterogeneity effect by sales volume. The unit of data is collectionid, week, and type.

	(1) Sales	(2) Price	(3) Revenue
BNPL_Top20_OS	-0.444***	-0.458	-1.499**
	(0.165)	(0.326)	(0.638)
BNPL_Top20_Blur	-0.528**	0.096	0.144
	(0.216)	(0.204)	(0.384)
BNPL_bottom80_OS	0.667***	0.089	1.347***
	(0.177)	(0.208)	(0.270)
BNPL_bottom80_Blur	1.392***	0.087	2.081***
	(0.214)	(0.208)	(0.346)
Constant	3.715***	7.016***	10.475***
	(0.049)	(0.054)	(0.099)
Observations	10214	10214	10214

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13 Heterogeneity effect by price. The unit of data is collectionid, week, and type.

	(1)	(2)	(3)
	Sales	Price	Revenue
BNPL_Top20_OS	0.178	-0.424	-0.311
	(0.307)	(0.279)	(0.821)
BNPL_Top20_Blur	1.541***	-0.121	2.373***
	(0.383)	(0.217)	(0.715)
BNPL_bottom80_OS	-0.093	0.099	0.702*
	(0.189)	(0.218)	(0.354)
BNPL_bottom80_Blur	0.429*	0.124	1.391***
	(0.219)	(0.215)	(0.395)
Constant	3.547***	7.286***	10.435***
	(0.050)	(0.059)	(0.110)
Observations	9594	9594	9594
Top 20 FE, Collectio FE, Week FE and Platform FE	Yes	Yes	Yes

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14 Heterogeneity effect by rarity. The unit of data is collectionid, week, and type.

	(1)	(2)	(3)
	Sales	Price	Revenue
BNPL_Top20_OS	0.347*	0.165	0.749***
	(0.180)	(0.196)	(0.272)
BNPL_Top20_Blur	0.689***	0.170	1.153***
	(0.186)	(0.200)	(0.355)
BNPL_bottom80_OS	0.186	0.183	0.617**
	(0.162)	(0.206)	(0.255)
BNPL_bottom80_Blur	0.355*	0.163	0.799**
	(0.211)	(0.204)	(0.375)
Constant	3.437***	7.185***	10.308***
	(0.049)	(0.052)	(0.100)
Observations	9560	9560	9560

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

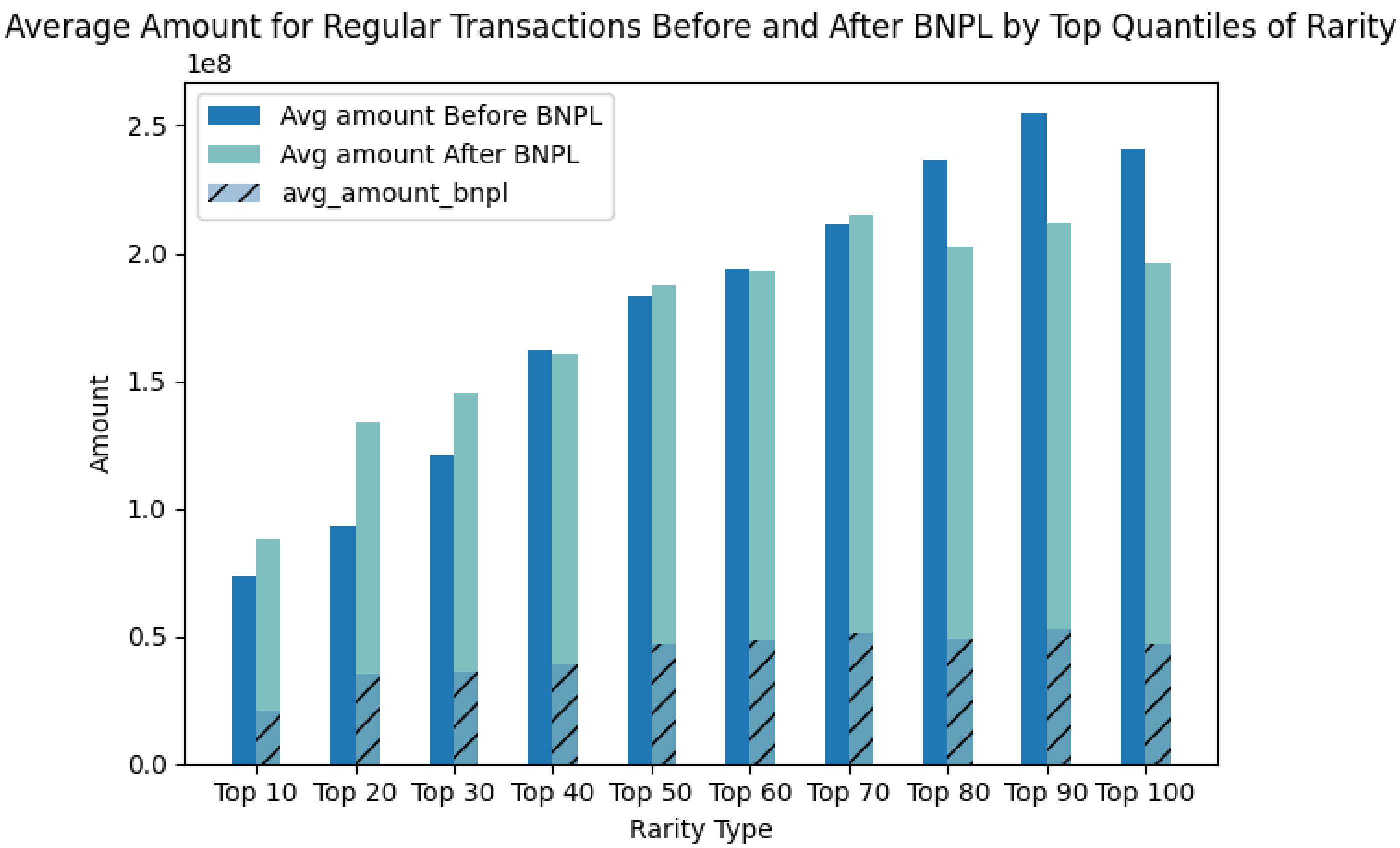

Figure 4 **Users spend on different Rarity tiers.**

6.1. Supply Side Mechanism:

Table 15 Impact of BNPL on listings. The unit of data is collectionid and week.

	(1) ListingsBlur	(2) ListingsOS	(3) Amount_listedBlur	(4) Amount_listedOS
DID	0.731**	0.644	0.124	1.328
	(0.285)	(0.571)	(0.327)	(0.907)
Staggered DID	0.753***	0.679	0.059	1.354
	(0.237)	(0.574)	(0.304)	(0.863)
Synthetic DID	0.758	1.225	0.144	2.587*
	(0.559)	(0.813)	(0.273)	(1.383)
Observations	2397	2397	2397	2397
Collection FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes

Clustered Standard errors by collectionid and week in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16 Heterogeneity effect by price. The unit of data is collectionid, week, and type.

	(1) Listing	(2) Amount
BNPL_Top20	-0.428	0.061
	(0.473)	(0.708)
BNPL_Top20_Blur	2.364***	1.539
	(0.522)	(1.238)
BNPL_bottom80	0.261	0.417
	(0.593)	(0.753)
BNPL_bottom80_Blur	2.270***	0.870
	(0.668)	(1.092)
Constant	2.477***	4.708***
	(0.068)	(0.076)
Observations	10406	10406

Clustered Standard errors by collectionid and week in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17 **Heterogeneity effect by Rarity. The unit of data is collectionid, week, and type.**

	(1) Listing	(2) Amount
BNPL_Top20	-0.552	0.043
	(0.476)	(0.765)
BNPL_Top20_Blur	2.065***	1.392
	(0.533)	(1.255)
BNPL_bottom80	0.076	0.470
	(0.614)	(0.795)
BNPL_bottom80_Blur	2.028***	0.221
	(0.662)	(1.028)
Constant	2.427***	4.836***
	(0.068)	(0.087)
Observations	9550	9550

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18 Impact of BNPL on Sales controlling number of listings

	(1) SalesBlur	(2) SalesOS	(3) RevenueBlur	(4) RevenueOS	(5) PriceBlur	(6) PriceOS
DID	0.423**	-0.000	0.948**	0.357	0.191	0.201
	(0.200)	(0.178)	(0.362)	(0.303)	(0.213)	(0.212)
Staggered DID	0.414**	-0.056	0.924***	0.272	0.185	0.193
	(0.200)	(0.183)	(0.341)	(0.317)	(0.214)	(0.216)
Synthetic DID	0.252	-0.074	0.972**	-0.105	-0.123	-0.062
	(0.216)	(0.203)	(0.464)	(0.423)	(0.172)	(0.166)
Observations	2499	2499	2499	2499	2499	2499
Collection FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19 **Impact of BNPL on Sales controlling Art, Membership and Gaming**

	(1) SalesBlur	(2) SalesOS	(3) RevenueBlur	(4) RevenueOS	(5) PriceBlur	(6) PriceOS
Panel A: Art						
DID	0.816***	0.155*	1.073***	0.405***	0.233***	0.247***
	(0.107)	(0.080)	(0.164)	(0.130)	(0.061)	(0.061)
Staggered DID	0.816***	0.119	1.058***	0.358***	0.218***	0.236***
	(0.103)	(0.077)	(0.157)	(0.125)	(0.062)	(0.060)
Synthetic DID	0.442*	0.044	0.966**	-0.167	-0.245	-0.304
	(0.258)	(0.199)	(0.475)	(0.349)	(0.228)	(0.251)
Panel B: Membership						
DID	0.528***	0.134*	1.873***	1.033***	0.285***	0.310***
	(0.097)	(0.067)	(0.191)	(0.146)	(0.060)	(0.057)
Staggered DID	0.517***	0.101	1.915***	1.028***	0.277***	0.305***
	(0.094)	(0.068)	(0.182)	(0.140)	(0.058)	(0.057)
Synthetic DID	0.607*	0.069	2.957***	1.683*	-0.107	-0.016
	(0.330)	(0.207)	(1.067)	(0.975)	(0.269)	(0.727)
Panel C: Gaming						
DID	0.174**	-0.152***	0.223	-0.076	-0.012	0.057
	(0.073)	(0.052)	(0.142)	(0.067)	(0.053)	(0.039)
Staggered DID	0.139*	-0.205***	0.168	-0.141*	-0.036	0.046
	(0.078)	(0.058)	(0.149)	(0.076)	(0.058)	(0.043)
Synthetic DID	0.214	-0.275	0.123	-0.246	-0.235	-0.082
	(0.318)	(0.175)	(0.357)	(0.296)	(0.189)	(0.204)

Clustered Standard errors by collectionid and week in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20 **Summary statistics for collection level balanced data.**

	Mean	SD	Min	Max	N
SalesBlur	3.74	2.02	0	9	2,499
SalesOS	3.54	1.17	0	9	2,499
RevenueBlur	9.98	4.20	0	18	2,499
RevenueOS	10.33	2.63	0	16	2,499
PriceBlur	6.31	2.46	0	12	2,499
PriceOS	6.85	1.95	0	12	2,499

Table 21 **Description and transformations applied to the variables.**

Variable	**Description**	**Transformations**
Users	Active addresses trading in the network	
Sales	weekly total number of NFT sales where users are the sellers eliminating washtraders	Total_sale - Washtraders
Actual_Sales	Weekly total number of NFT sales eliminating the washtrading	$ln(Actual\_Nft\_sales + 1)$
Revenue	Amount generated by NFT sale in that week by the collection	$ln(Revenue + 1)$
Actual_Sales_Blur	Weekly total number of NFT sales on blur platform, eliminating the washtrading	$ln(Nft\_sales\_blur + 1)$
Actual_Sales_opensea	Weekly total number of NFT sales on opensea platform, eliminating the washtrading	$ln(Nft\_sales\_opensea + 1)$
Revenue_Blur	Amount generated by NFT sale in that week by the collection on Blur platform	$ln(Revenue\_blur + 1)$
Revenue_opensea	Amount generated by NFT sale in that week by the collection on Opensea platform	$ln(Revenue\_opensea + 1)$

7. Plots

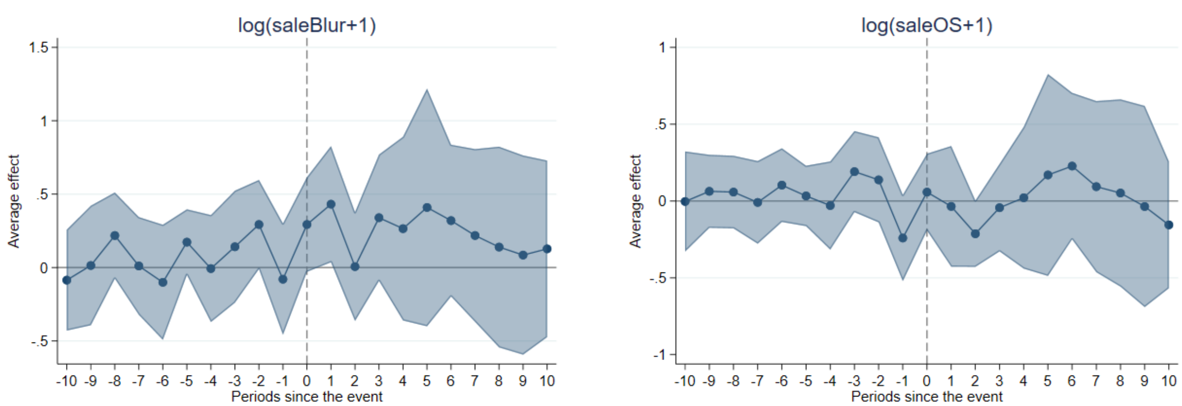

Figure 5 **Estimated Treatmenent Effect by Period .**

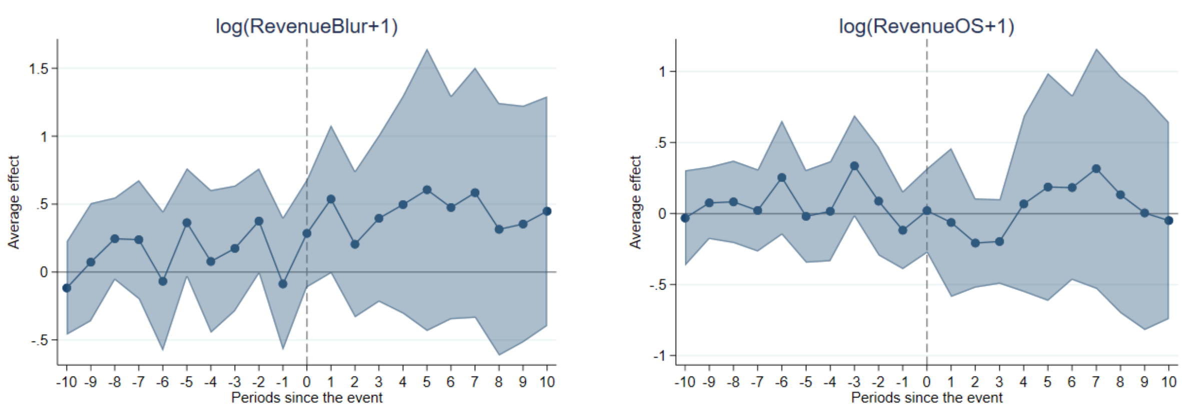

Figure 6 **Estimated Treatmenent Effect by Period .**

References

(2023) What is blur nft marketplace? URL https://www.datawallet.com/crypto/what-is-blur-nft-marketplace#:~:text=Blur.io%20is%20an%20NFT,more%20to%20professional%20NFT%20traders.

Arkhangelsky D, Athey S, Hirshberg DA, Imbens GW, Wager S (2021a) Synthetic Difference-in-Differences. *American Economic Review* 111(12):4088–4118, URL http://dx.doi.org/10.1257/aer.20190159.

Arkhangelsky D, Athey S, Hirshberg DA, Imbens GW, Wager S (2021b) Synthetic difference-in-differences. *American Economic Review* 111(12):4088–4118.

Butts K, Gardner J (2021) {did2s}: Two-stage difference-in-differences. *arXiv preprint arXiv:2109.05913* .

Callaway B, Sant'Anna PHC (2021) Difference-in-Differences with multiple time periods. *Journal of Econometrics* 225(2):200–230, ISSN 0304-4076, URL http://dx.doi.org/https://doi.org/10.1016/j.jeconom.2020.12.001.