Chasing Market Growth and Matching Efficiency in Two-Sided Platforms: Evidence from the Lazy-Minting Policy in an NFT Marketplace

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Abstract. A common challenge faced by two-sided marketplaces is to expand the market while ensuring efficient matching of the two sides. We study a new platform growth strategy that increases *market thickness* with free entry while allowing suppliers to discretionarily *signal their quality* to buyers, thus forming a tiered market structure that maintains high matching efficiency even as the market grows. We use a real-world example of this growth strategy in the context of non-fungible token (NFT) markets, in which suppliers could choose to delay the payment of NFT creation fees (i.e., market entry costs) until the moment when an NFT is sold (*lazy minting*), or make this payment up front at the time of NFT creations (*gas minting*). We use the difference-in-differences strategy to identify the impact of this lazy-minting policy on matching efficiency. We find that, although the introduction of lazy minting reduces the average matching likelihood of an NFT by 45.5%, it increases the gas-minting segment's matching likelihood by 116.9% and first-sale price by 126.5%. We establish that suppliers opt for gas minting, based on their high-quality creations, and that choosing gas minting enables them to signal high quality to buyers, resulting in improved matching likelihood and higher first-sale prices. Overall, this new growth strategy benefits the platform due to increased sales and higher commission revenues. Our study establishes the value of a new platform growth strategy that allows entrants to self-select their entry costs, thereby shaping a tiered market segmentation with an effective quality-signaling mechanism.

Keywords: platform growth, quality signaling, market thickness, lazy minting, NFT marketplaces, difference-in-differences

1. Introduction

The success of a two-sided platform hinges on the size of its two-sided network. As such, scaling has quickly become a widely accepted motto in platform economics and practice (Cennamo and Santalo 2013). For instance, many major e-commerce retailers, such as Amazon.com, achieve rapid growth by forming partnerships with third-party merchants (Chen and Guo 2022). Many peer-to-peer platforms, such as Kickstarter in crowdfunding, grant users unlimited access to launching new campaigns to attract broader participation (Geva et al. 2019). Such a platform growth strategy has been termed *get big fast* (GBF; Cennamo and Santalo 2013). Although the GBF strategy has merit, unrestrained expansion can congest the platform (Roth 2008) and undermine platform performance due to the overwhelming presence of low-quality offerings and high friction in matching the two sides of the platform (Geva et al. 2019, Li and Netessine 2020).

Considering the potential conflict between rapid market growth and deteriorated matching efficiency, platforms have explored variants of the GBF strategy. One approach is to grow the network strategically by imposing tight restrictions and quality controls over entry (Oliva et al. 2003, Hagiu 2009, Boudreau 2010, Casadesus-Masanell and Hałaburda 2014, Yang et al. 2021). Nintendo, in the 1980s, for example, introduced its "Seal of Quality" policy by enforcing stringent publishing guidelines for third-party game developers to ensure the quality of each game.[1] Ensuring high-quality growth, however, comes at the expense of offering fewer market items, which could be detrimental for platform development in the long run (He and Goh 2022). Moreover, the cost of quality certification can be prohibitive when the platform has to manually review and assess each participant's quality, as Nintendo did. An alternative approach is to exercise quality control through user-generated content, such as online reviews, to help buyers to differentiate between high- and low-quality products, thereby facilitating supply-demand matching. Delegating quality control to reviewers, however, may result in review manipulation (Nie et al. 2022), quality misrepresentation (Pu et al. 2022), or the "cold-start" problem in terms of new products' being discovered and reviewed by consumers (Pallais 2014, Burtch et al. 2021). Further, reviews may not be informative or feasible for markets with unique and personalized product offerings (e.g., collectibles, artworks) due to the lack of multiple copies of the same product.

This paper explores a new platform growth strategy that aims to achieve market growth and matching efficiency in a novel way. The key idea is to provide an option for the entrants to incur different entry costs, which allows them to signal their product quality. Those who do not want to incur an entry cost

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[1] See https://gamicus.fandom.com/wiki/Nintendo_Seal_of_Quality. Apple also practices similar quality review process to avoid erosion of platform quality, https://developer.apple.com/app-store/review/guidelines/#after-you-submit (accessed September 10, 2022).

can still enter the market but cannot signal high quality. The availability of low entry costs empowers market growth, whereas the more expensive entry option signals quality and creates a tiered market that can simplify product discovery, thus making matching more efficient. Further, such an approach works better for markets with unique products because it leverages a supplier's private knowledge of (or belief in) the product's quality, which is more cost effective than the case in which platforms have to determine the quality of each entrant.

We identify a recent application of this market growth strategy in the domain of non-fungible token (NFT) artwork marketplaces. Typically, NFT creators pay an upfront fee on Ethereum (i.e., minting fee in the form of Ethereum gas, at an average of $82) to create (mint) an artwork on NFT marketplaces (e.g., OpenSea, Foundation, Rarible). Considering that most NFT creators never sell their NFTs,[2] paying an upfront minting fee hinders the supply of NFTs and represents an entry barrier. A new NFT minting policy, termed *lazy minting*, was introduced by Rarible.com to address this issue by offering a free market entry option. Specifically, lazy minting defers the fee payment until the time of an NFT's first sale (no gas-fee payment if there is no sale), which significantly lowers the entry barrier for creators and boosts NFT supplies.

Although removing the entry barrier would likely enlarge market size, it also would adversely impact matching efficiency in two-sided marketplaces due to the proliferation of choices and the concomitant search friction (Fradkin et al. 2015, Dinerstein et al. 2018, Geva et al. 2019, Li and Netessine 2020). Further, a low entry barrier may inadvertently attract incapable or opportunistic creators who do not exert adequate efforts in making NFTs (e.g., many NFTs are simply pictures downloaded from the Internet). This can potentially lead to a type of market failure known as Gresham's Law, whereby "bad money drives out good" (Akerlof 1970), leaving the NFT platform crowded with low-quality NFTs. This will take a toll on the buyer side as well because buyers may have difficulty in discerning valuable NFTs from a swarm of low-quality ones in an overly thick market.

The interesting point about the lazy-minting policy is that Rarible makes lazy minting optional. Creators can still decide whether to pay the minting fees up front (*gas minting*) or later (*lazy minting*). We find that, even after lazy minting becomes available, some creators still opt for gas minting. This leads to the following questions: What is the motivation for creators to choose the costly gas minting channel even when a free option is available? Why, then, do creators not use lazy minting to enter the market freely? To answer these questions, we posit that this optional lazy-minting policy establishes a quality signaling mechanism for the NFT market. High-quality creators can choose to pay up front to signal their quality,

[2] See https://protos.com/elite-five-percent-nft-traders-make-vast-majority-opensea-profits/. Notably, 5% of NFT traders have received 80% of the profits on the OpenSea marketplace, and 73% of the NFTs were never sold.

akin to the idea of "money burning" in the advertising literature, which has documented that high-quality sellers invest more up front in advertising compared to low-quality ones (Kihlstrom and Riordan 1984, Milgrom and Roberts 1986, Kirmani and Rao 2000). This self-selection option in the market design creates a separating equilibrium where differentiated creators of varying NFT qualities can exercise discretion in choosing different minting actions. Further, due to the separating equilibrium, buyers can efficiently target their search to only the high-quality submarket comprised of gas-minted NFTs, thereby reducing search friction and increasing the efficiency of matching, particularly in the gas-minting market segment.

Given the aforementioned counteracting effects, it is unclear whether introducing a policy such as lazy minting improves or hinders matching efficiency. Our first research objective aims to address this by investigating the impact of such a new platform growth strategy on the matching efficiency of the platform, measured by how likely an NFT is to receive a match/sale and how much it can be sold for. Further, the impact may be heterogeneous on different segments of the market, such as the gas-minting segment (which comes from the costly entry channel), as opposed to the entire market. Our second research objective centers on this heterogeneous effect, for which we analyze the lazy-minting policy's differential impacts on the gas-minting segment vs. the entire market. Our third research objective is to investigate, based on the establishment of a separating equilibrium, whether the quality signaling mechanism is attainable for the gas-minting segment and to explore the heterogeneous effects that arise due to the inherent tension between the market thickness mechanism and quality signaling mechanism. In pursuit of these three objectives, we also analyze whether it is beneficial for the platform to adopt the policy by comparing the overall profits and the total number of sales of the platform before and after implementing the policy.

We leverage the introduction of the lazy-minting policy on Rarible to empirically examine the impacts of this new market-growth strategy. On October 18, 2021, Rarible introduced the lazy-minting option, allowing creators to pay minting fees after the first sale. We consider Rarible as the treated platform and identify a comparable control platform, Foundation, which mandates gas minting. We collect six-month data (from August 2021 to February 2022) on both platforms and apply a difference-in-differences (DID) identification strategy. We find that the overall matching likelihood decreases by 45.5% after the introduction of the lazy-minting policy but increases by 116.9% in the subgroup of gas-minted NFT artworks. In addition, the first-sale price increases by 126.5% for gas-minted NFT artworks but is unchanged in the entire market. To explain the underlying mechanisms, we draw on market thickness and quality signaling theories. Due to the influx of low-quality, lazy-minted artworks, the increase in market thickness leads to higher search friction, reducing the overall matching efficiency (Li and Netessine 2020). The ability to signal high quality through gas minting, however, results in better matching outcomes in the gas-minting segment. The net impact of the two mechanisms is overall positive: The entire marketplace sees more sales and enjoys higher revenues after the introduction of lazy minting.

Our study provides implications for the emerging two-sided marketplaces by investigating a critical market growth problem. Although the literature recognizes the fallacy of the popular GBF strategy (Lee et al. 2006, Sterman et al. 2007, Boudreau 2012) and the pitfalls of thick markets (Bimpikis et al. 2020, Li and Netessine 2020, Arnosti et al. 2021), in practice, platforms typically rely on conservative growth strategies (Sterman et al. 2007, Yang et al. 2021) with controlled market size to mitigate the problems (Bimpikis et al. 2020, Arnosti et al. 2021, Hou et al. 2021). We contribute to this literature by theorizing and testing a potential win-win platform growth strategy that can substantially grow market size while improving matching efficiency and generating higher revenues for the platform.

2. Literature Review

Our study is closely related to the literature that studies platform growth with increased market thickness and quality signaling in two-sided markets. Here, we review both strands of literature.

2.1. Platform Growth and Market Thickness

There is a burgeoning body of literature on the market-expansion strategies used by two-sided platforms to grow their market sizes. Examples of these strategies include price subsidizing (Parker and Van Alstyne 2005), consolidating and merging competing platforms (Farronato et al. 2020, Li and Netessine 2020), enhancing compatibility, forming partnerships with competitors or complementors (Adner et al. 2020, Sharma and Mehra 2021), and opening platforms to third-party vendors (Song et al. 2020, Chen and Guo 2022), among others. The common idea behind these strategies is to rapidly acquire as many users as possible (i.e., the GBF strategy) to quickly grow the platform with a large user base (Cennamo and Santalo 2013, Yang et al. 2021), which is believed to be the key to a platform's survival and competitive advantage in the platform economy.

Although the success stories of platforms such as Amazon lend credence to the GBF strategy, there also is debate over its adverse consequences. GBF typically leads to a thick market with a large number of participants. Such a thick market has the potential to facilitate more matches due to the richness of supplies and the high heterogeneity of demand (Katz and Shapiro 1985, He and Goh 2022). A thick market, however, does not necessarily ensure high matching efficiency. For example, rampant platform growth may attract a large number of low-quality suppliers, leading to overcapacity (Sterman et al. 2007) and the inability to fulfill demand with high service quality (Oliva et al. 2003). In addition, the presence of an overwhelming number of choices can exacerbate the difficulty of product and price discovery for buyers (Koulayev 2014, Arnosti et al. 2021). This is also documented by Ghose et al. (2014), who find that providing more choices may cause buyers to make fewer purchases, owing to information overload. Similarly, Li and Netessine (2020) observe a decreased matching rate due to the increased search friction caused by a platform-integration policy with a ballooned market.

To alleviate the problems associated with market thickness during platform expansions, scholars have examined and proposed a variety of approaches. A popular approach is to constrain the market size by limiting the number of available choices (Hagiu 2009, Casadesus-Masanell and Hałaburda 2014, Bimpikis et al. 2020) or imposing market entry and participation restrictions (Arnosti et al. 2021, Hou et al. 2021). Boudreau (2010) and Hagiu (2009) suggest that, instead of embracing an all-encompassing openness, quality controls should be imposed on the supply side to regulate suppliers' access to the platform. Related to this approach, Yang et al. (2021) elaborate on a scheme whereby platforms should grow by targeting only average-quality firms. Other approaches include promoting the most desired or lowest-priced products to consumers (Dinerstein et al. 2018); designing interactive decision tools, such as recommendation and reputation systems (Häubl and Trifts 2000, Einav et al. 2016, Tadelis 2016, Ashlagi et al. 2020, Bimpikis et al. 2020); and disclosing richer marketplace information, such as demand information (Huang et al. 2022), availability information (Horton 2019), preference information (Bapna et al. 2016, Ashlagi et al. 2020, Horton et al. 2021), and quality information (Dimoka et al. 2012, Tadelis and Zettelmeyer 2015, Geva et al. 2019), among others. These approaches, however, are generally costly for platforms and cannot be easily applied to newly established platforms or those that sell unique products. Our study contributes to this stream of literature by investigating a novel and cost-effective platform growth strategy that couples market expansion with a unique opt-in, quality-signaling feature to manage market thickness.

2.2. Quality Signaling

Our study also is related to the literature on signaling theory. Akerlof (1970) shows the possibility of market failure when buyers cannot distinguish high-quality sellers from low-quality ones, or "lemons," due to information asymmetry. To mitigate information asymmetry and prevent market collapse, sellers can proactively transmit quality signals to consumers, thereby restoring market efficiency (Spence 1973). Some signaling examples include pricing (Milgrom and Roberts 1986), money-back guarantees (Moorthy and Srinivasan 1995), hassle-free return insurance (Zhang et al. 2022), third-party certification and assurance (Gao et al. 2010, Dimoka et al. 2012), advertising (Nelson 1974, Kihlstrom and Riordan 1984, Milgrom and Roberts 1986, Feng and Xie 2012, Joshi and Musalem 2021), and so forth. According to the categorization in Kirmani and Rao (2000), our specific example, the gas-minting quality signal, is a type of sale-independent signal, meaning that the cost of the quality signal is spent up front, regardless of whether future sales occur. The rationale behind this type of signal is that a high-quality seller, which has invested a high amount of money and effort up front, correctly believes that it can recover the upfront costs via future sales, unlike a low-quality seller.

The signaling literature has documented the efficacy of platform-created quality-signaling designs. For example, Horton (2019) examines an opt-in signaling feature in an online labor market that allows workers to self-reveal their availability. This approach avoids wasted solicitation and reduces the probability of rejection, thus increasing the matching likelihood. The follow-up work by Horton et al. (2021) investigates an employer-side signaling mechanism where employers signal their preference and willingness to pay for workers' quality/ability. The study shows that this signaling mechanism helps potential employees to better target the "right" employers, thus improving market matching efficiency.

In line with this stream of literature, our study also investigates an opt-in quality signaling design on the supply side. In our study, what is unique is that opting for quality signaling creates a market entry barrier for the suppliers because signaling quality is costly. Although quality signaling has been well studied in various settings, it has rarely been connected with entry barriers or examined in the market growth context. Its effectiveness as a part of a market growth strategy, therefore, is largely understudied. Theoretically, our research extends the extant studies by connecting the literature on platform growth with that on quality signaling to investigate the joint effects of market thickness and quality signaling when they are embedded in the same market growth strategy.

3. Empirical Context and Data

3.1. Research Setting

Our research setting is two-sided platforms for NFT trading between buyers and sellers/creators. An NFT indexes a unique digital asset represented by its metadata content, such as asset name, creator, creation time, description, and appearance, which are permanently stored on Blockchain. NFT marketplaces enable participants to mint (create) NFTs, showcase their inventory, and sell their NFTs. In addition, Blockchain enables a transparent, indisputable, and immutable provenance that pertains to each NFT by recording the NFT's complete event history (Nadini et al. 2021). An example of an NFT's history (including the minting activity and all trading transactions) is shown in Figure 1.

The Ethereum Blockchain, where most NFTs are created, charges NFT creators an upfront gas-minting fee each time they mint a new NFT. This fee is used to compensate Ethereum miners and validators for the computational resources that they spend to validate and record each minting activity. Typical gas-minting fees range from $50 to $200, depending on the complexity of the minting transaction and real-time traffic on the Ethereum network. Thus, the gas-minting fee imposes a substantial cost on creators and represents a barrier to market entry.

We leverage an empirical opportunity of the lazy-minting policy, which was launched by Rarible (the second largest NFT platform) on October 18, 2021, to eliminate the entry barrier.[3] All of the NFTs created prior to this time had to pay their gas fees up front at the time of minting, referred to as *gas minting*. Under the lazy-minting option, however, NFT creators do not pay gas fees up front at the time of minting;

[3] See https://rarible.medium.com/create-nfts-for-free-on-rarible-com-via-a-new-lazy-minting-feature-91cb4b7c68e6.

rather, this fee is collected later at the time of an NFT's first sale.[4] This new minting policy, thus, greatly lowers the entry barrier, given that most NFTs on Rarible (92.3% in our sample) never get sold. As a result, the number of NFTs on Rarible climbed sharply from 8,024 in the last month before the policy change to a total of 289,046 in the first month after the policy change (i.e., an increase of 36 times). Although this policy helps Rarible to grow the supply side, the problem of increased search friction could potentially offset the benefits brought by the market growth.

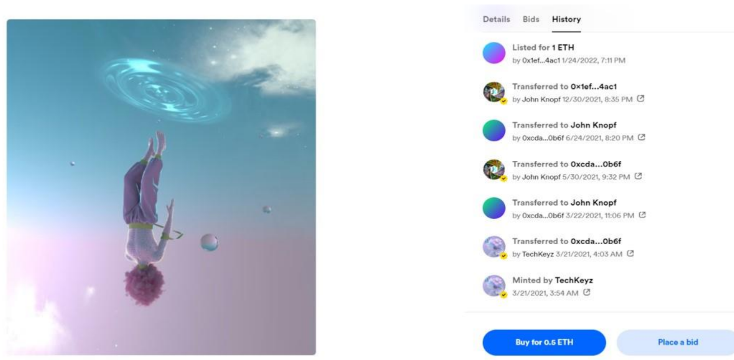

Figure 1. Example of an NFT Provenance: Minting and Trading History

Notably, Rarible made the policy optional to creators: They could still choose between gas minting and lazy minting. The choice of whether an NFT is gas-minted or lazy-minted is recorded in the metadata of the NFT and stored in the Blockchain, thus making it transparent to market participants. As a result, two segments of NFTs are formed based on the choice made by their creators. If the choice of paying the gas fee up front (i.e., gas minting) creates a credible signal of quality, such a signal may mitigate the negative effect of search friction or even realize higher matching efficiency by making it easier for the demand side to find the right NFTs. Therefore, the *introduction of lazy minting as an option for NFT creators* by Rarible presents us with a unique opportunity to study the novel market growth strategy that may increase market size and matching efficiency simultaneously. Accordingly, we take the NFTs created on Rarible as the treatment group.

To estimate the impact of the lazy-minting policy, we identify another NFT marketplace, Foundation.app, as the control/counterfactual group. We select Foundation as the control platform for two reasons. First, Foundation is also an Ethereum-based NFT marketplace, and it mandates gas minting throughout our observation period. Second, according to the NFT marketplace ranking by Dappradar.com

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[4] For a lazy-minted NFT, the gas fee is postponed until the first sale occurs, and the sale mechanism determines who pays the gas fee (see Footnote 8 for further details). If it is sold via accepting bids in auctions, the deferred gas fee will be paid by creators. If it is sold through a fixed-price sale, however, the first buyer will pay the deferred gas fee.

(as shown in Figure A1 in Appendix A), Foundation is the closest artwork marketplace to Rarible in terms of the total number of traders and the total transaction volume.[5] We thus compare the market performance of NFTs listed in these two platforms to examine how the introduction of the lazy-minting policy influences market matching efficiency. To make a clear distinction between the treatment and control groups, we exclude creators who multi-home between the two platforms (i.e., creators who create artworks on both Rarible and Foundation).

3.2. Data

We use the public application programming interfaces (APIs) provided by the two platforms to collect data on all NFT artworks that were created between August 16, 2021, and February 7, 2022. As a result, our data span 25 weeks, with 9 weeks of pre-treatment data and 16 weeks of post-treatment data for both platforms. Figure 2 provides a summary of the research timeline. The data contain the metadata on each artwork's token identifier; the creator's Ethereum address; NFT descriptions; minting type (i.e., lazy or gas minting); number of likes; sale mechanism, which can be either buy-now sale or auction-based sale; NFT type (i.e., video or image); and so forth. We also trace the complete provenance history of minting, listing, bidding, buying, and selling activities for each artwork. Each provenance record indicates the activity type, activity timestamp, transaction price (if any), and Ethereum wallet address of the participants.

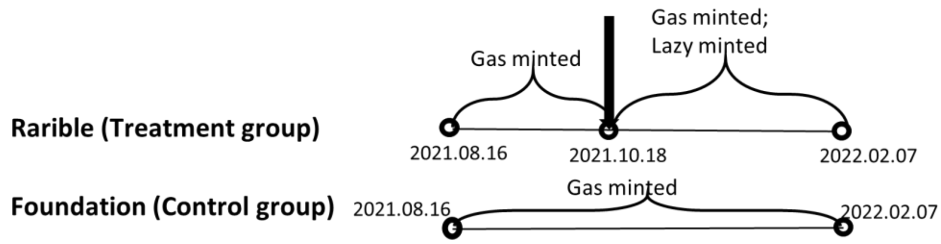

Figure 2. Research Setting and Timeline

3.3. Variables

We measure matching efficiency at the NFT level through two aspects.[6] The first variable is matching likelihood, operationalized as a dummy variable that indicates whether an artwork was sold within 30 days after its creation time.[7] This variable reflects how easily a match can be achieved for an NFT by capturing the average matching efficiency of the platform. As a result, we drop the last 30-day NFT data

[5] See https://dappradar.com/nft/marketplaces/protocol/ethereum (accessed October 22, 2022).

[6] We are particularly interested in the first-sale matching efficiency of the primary market (i.e., artworks listed by the creator and purchased by the first collector) because the choice of lazy minting or gas minting is made by the creator, who is normally the first seller of the artwork.

[7] To make the sale outcomes comparable between newly created NFTs and NFTs created earlier, we consider 30 days after each NFT's creation time as a reasonable time window for the first sale to happen. This time window covers most sales, as 83% of the sold NFTs were sold to their first buyers within 30 days after their creation.

because we do not have adequate time to observe the complete sale activities for these NFTs. After this adjustment, the post-treatment periods contain 84 days across 12 weeks.

The second outcome variable that we construct is the first-sale price for each NFT sold. To control for the unstable value of cryptocurrencies and make sale prices comparable, we map each sale price in ETH or other cryptocurrencies (e.g., RARI, DAI, USDC) to its corresponding USD closing price on the day of sale. This variable reflects the value of an NFT conditional on a sale.

We present the definition and descriptive statistics of the key variables in Table 1. We will discuss them in detail when we use them in the relevant empirical analyses. We apply a natural logarithm transformation on variables with high skewness. We also provide descriptive statistics on Rarible's gas-minted and lazy-minted NFTs separately in Table 2. Notably, we observe a tale of two stories. The gas-minted NFTs created after the treatment have a higher average matching likelihood and higher first-sale prices than do those created before the treatment, whereas the lazy-minted NFTs experience lower matching rates and lower sale prices on average.

Table 1. Summary Statistics

Variable	Description	Obs.	Mean	Std. Dev.
Main Dependent Variables				
Matching likelihood	Equal to 1 if an NFT had its first sale within 30 days since its creation	1,355,640	0.015	0.121
ln(first-sale price)	First-sale price (in USD) of a sold NFT	20,182	7.053	1.428
Control Variables				
Fixed sale	Equal to 1 if an NFT is listed by fixed-price sale	1,355,640	0.699	0.459
NFT type	Equal to 1 if an NFT is of the video type	1,355,640	0.095	0.293
Variables For Mechanisms				
No. of creations per day	Number of creations each creator created per day	29,466,297	0.046	4.773
ln(minimum asking price)	Minimum asking price set by the creator for an NFT	1,130,233	5.359	2.535
Adjust asking prices or not	Equal to 1 if an NFT's listed prices were once adjusted during the 30-day sale time window	1,130,233	0.126	0.332
Ratio of markdown adjustments	Ratio of markdown price adjustments to the total number of price adjustments	142,662	0.871	0.294
ln(no. of days to match)	Number of days taken for a match to happen since the creation of an NFT	20,182	1.406	0.918
ln(no. of bids)	Number of bids each buyer placed each week	281,086	0.063	0.283
ln(no. of bids per match)	Number of bids each buyer placed each week to secure a match	17,086	0.961	0.453
No. of likes per day	Average number of likes received per day for an NFT	1,355,640	0.023	0.151
ln(maximum bidding price)	Maximum bidding price for an NFT	20,977	5.858	2.659

Selling experience	Total count of historical sales of an existing creator who had created NFTs before the treatment	98,101	10.065	57.180
Platform-level Variables				
Matching rate	Ratio of NFTs sold within 30 days out of all the NFTs created on the same day on the platform	294	0.212	0.186
Total no. of matches	Total number of NFTs created in a day and sold within the next 30 days on the platform	294	68.646	47.139
ln(commission revenue)	Platform-level revenue from commission fees of all the sold NFTs created in one day	294	9.232	1.675

Note. To be consistent with the empirical analyses, we report the *ln*(*x+1*) values for these log-transformed variables, with the exception of commission revenue as transformed by *ln*(*x*).

Table 2. Summary Statistics for the Two Groups of NFTs on Rarible

Variable	Pre-Treatment Gas-Minted NFTs		Post-Treatment Gas-Minted NFTs		Post-Treatment Lazy-Minted NFTs	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Matching likelihood	0.077	0.266	0.131	0.338	0.001	0.034
ln(first-sale price)	6.144	1.867	7.548	1.793	5.513	2.412
Fixed sale	0.468	0.499	0.518	0.500	0.727	0.445
NFT type	0.090	0.286	0.155	0.362	0.089	0.285
ln(minimum asking price)	6.280	2.634	6.645	2.458	5.274	2.543
Adjust asking prices or not	0.338	0.473	0.294	0.456	0.120	0.325
Ratio of markdown adjustments	0.780	0.341	0.611	0.441	0.876	0.290
ln(no. of days to match)	1.103	1.027	1.329	0.955	1.210	1.140
No. of likes per day	0.042	0.130	0.080	0.270	0.014	0.093
ln(maximum bidding price)	2.232	2.057	4.575	2.217	2.325	2.117

4. Empirical Strategy and Results

4.1. Empirical Model

We leverage the policy shock of lazy minting on Rarible by employing the DID identification strategy. Our setting mimics a quasi-experiment in which NFTs created on Rarible serve as the treatment group, while NFTs created on Foundation serve as the control group to reflect the natural trend of NFT markets. Given that each NFT is minted only once, we only observe the 30-day matching outcome of each NFT only once; thus, our data are repeated cross-section (RCS) data of unique NFTs minted at different times. As such, our data do not conform to a typical panel dataset (in which the same unit is observed across time in both the pre-and post-treatment periods), and, accordingly, the DID estimation is computed by comparing the matching efficiencies of different NFTs that are created before and after the lazy-minting policy (rather than the same NFTs before and after the policy). Although DID is commonly applied to panel datasets, it is also widely used for RCS data in the literature (Pischke 2007, Venkataramani et al. 2017, Sant'Anna and Zhao 2020). We construct a sample of 1,355,640 NFTs on the two platforms across 147 days (21 weeks), and each NFT appears once as a unique observation. We then apply the following econometric specification as our main model:

$$Y_{ijt} = \beta_0 + \beta_1 Post_t \times Treated_{ij} + \beta_2 Fixed\ Sale_i + \beta_3 NFT\ Type_i + v_j + u_t + \epsilon_{ijt}, \quad (1)$$

where i denotes one NFT, j indexes the platform, and t represents the day when NFT i was created. Each i is associated with one j and one t only. The main outcome variables of interest include (1) matching likelihood (binary) and (2) first-sale price within 30 days, which is log-transformed by *ln*(*first-sale price+1*). The dummy variable $Post_t$ equals 1 if day t occurs after the introduction of lazy minting (i.e., October 18, 2021), and 0 otherwise. $Treated_{ij}$ equals 1 if artwork i was created on Rarible, and 0 if created on Foundation. The treatment effect of the lazy-minting policy is captured by β_1. In addition, we control for the sale mechanism to account for the possible effect of different sale types on sale outcomes by adding $Fixed\ Sale_i$, which is equal to 1 if creation i was listed by the fixed-price sale, and 0 if by auction.[8] We also control for the digital format of each NFT by a dummy variable $NFT\ Type_i$, which equals 1 if artwork i is of the video type, and 0 if it is of the image type. v_j controls for the platform fixed effects, capturing platform time-invariant characteristics that might influence NFT sales (e.g., platform commissions). u_t controls for the day fixed effects, allowing us to better isolate the time-specific confounding factors, such as cryptocurrency daily price fluctuations and the overall supply/demand dynamics. $Post_t$ and $Treated_{ij}$ are included in Specification (1) and their effects have been absorbed by the day fixed effects and platform fixed effects, respectively. ϵ_{ijt} denotes the error term. Throughout the paper, we cluster the standard errors at the day level to account for markets' dynamics.

4.2. Main Results

We first examine the treatment effect of the lazy-minting policy on the entire market, i.e., including gas-minted NFTs and lazy-minted NFTs. We run Specification (1) and report the results in Table 3, Columns (1) and (2). The estimated coefficient of the DID variable suggests a negative and significant treatment effect of the lazy-minting policy on matching likelihood. Specifically, NFTs created on Rarible had an absolute 0.035 lower matching likelihood after the introduction of lazy minting. This translates to a decreased rate of 45.5% (0.035/0.077) because the average matching likelihood for Rarible NFTs before the treatment is 0.077. The impact of lazy minting on the first-sale price is negative but non-significant.

We further conduct a subsample analysis of the gas-minted NFTs (i.e., excluding all of the lazy-minted NFTs in the post-treatment period) to examine the heterogeneous impact of the lazy-minting policy on the gas-minting segment using Specification (1). We focus on this subsample because we expect the

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[8] The two platforms apply the same two types of sale mechanisms. The first type is an auction with a seller/creator-specified reserved price, which is the minimum amount that the creator is willing to sell an NFT for. All bids must meet or exceed the reserved price, and the highest bid wins the auction. The second type is a fixed-price sale or buy-now sale for which creators list their artworks at fixed prices to allow prospective buyers to acquire the NFTs right away. Buyers can still place bids lower than the fixed price, but then they have to wait for the creator to decide on whether to accept the highest bid.

gas-minting segment to behave differently from the lazy-minting segment as well as the entire market, as choosing gas minting can serve as a credible signal of quality because creators who mint relatively high-quality NFTs would be more willing to pay gas fees up front. Further, with the high-quality signal, gas-minted NFTs also would be more likely to be appreciated/recognized by buyers. Accordingly, this segment should perform better than it did previously, when no such quality-signaling option existed. Table 3, Columns (3) and (4), confirm our conjecture. The matching likelihood of gas-minted NFTs on Rarible increases by 0.090 after the introduction of lazy minting, which corresponds to a 116.9% increase rate (0.090/0.077). Moreover, the first-sale price also exhibits a statistically significant increase rate of 126.5%. Compared with the results in Columns (1) and (2), the gas-minting segment is better off after lazy minting becomes available. This observation suggests that the quality signaling effect may be of greater salience than the market thickness effect for the gas-minting segment.

Table 3. The Treatment Effect of Lazy-Minting Policy on Matching Efficiency

	(1)	(2)	(3)	(4)
Variable	*Matching Likelihood*	*First-Sale Price (ln)*	*Matching Likelihood*	*First-Sale Price (ln)*
Sample	Full NFT Sample	Sold NFT Sample	Gas-Minted NFT Sample	Sold Gas-Minted NFT Sample
$Post_t \times Treated_{ij}$	-0.035***(0.009)	-0.138 (0.140)	0.090*** (0.012)	1.265*** (0.157)
$Fixed\ Sale_i$	0.006*** (0.001)	0.427*** (0.063)	0.155*** (0.009)	0.373*** (0.064)
$NFT\ Type_i$	0.006*** (0.001)	0.100*** (0.031)	0.032*** (0.005)	0.054* (0.029)
Platform Fixed Effects	YES	YES	YES	YES
Day Fixed Effects	YES	YES	YES	YES
No. of Observations	1,355,640	20,182	75,444	18,679
No. of Clusters	147	147	147	147
Adjusted R-squared	0.301	0.148	0.142	0.133

Notes. $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01. Robust standard errors are clustered at the day level in parentheses.

4.3. Parallel Trends

The validity of the DID identification strategy hinges on the parallel-trends assumption (Angrist and Pischke 2009). In this context, artworks on Rarible and Foundation should experience similar trends in matching efficiency before lazy minting was introduced, making the additional difference in matching efficiency between artworks on Rarible and Foundation after the treatment attributable to the introduction of lazy minting. We use a relative time model to test whether NFTs created on Rarible and Foundation follow parallel trends before the treatment and report the results in Appendix B. All of the pre-treatment relative time dummies are statistically insignificant, and there is no clear trend before the treatment, suggesting the validity of the parallel-trends assumption.

5. Mechanisms

Drawing upon the theories on *market thickness* and *quality signaling*, we posit that the impacts of the new market growth strategy (i.e., lazy-minting policy) depend on the relative influence of these two countervailing mechanisms. On the one hand, the introduction of the lazy-minting option allows all creators to enter the market without paying the upfront gas fees, potentially attracting NFTs even with a low chance to be sold. This directly increases the thickness of the NFT market on the supply side (e.g., as measured by the number of creators and artworks). In turn, the increased market thickness would intensify supply-side price competition, prompting sellers to lower their asking prices (Tucker and Zhang 2010).

In addition, a thicker market could influence demand-side behavior. Having too many available choices may overwhelm buyers by increasing their cognitive burden when evaluating the sheer number of offerings (Iyengar and Lepper 2000, Koulayev 2014, Geva et al. 2019). Buyers may have to examine more alternatives before finding a match, exacerbating their market search friction (Li and Netessine 2020). As a response to intensified friction, buyers may tend to bid more to capture a potential match. In all, due to the intensified friction on both sides of the market, sellers/buyers may receive fewer matches, and it may take a longer time for them to achieve a match, leading to overall deteriorated matching efficiency.

On the other hand, the quality signaling mechanism could have the opposite effect. The co-existence of the two minting methods enables creators to signal the quality of each artwork. Creators of high-quality artwork would have the option to strategically choose gas minting to signal their willingness to pay for the upfront gas fee because they believe that their NFT has a higher chance of getting sold to recover the minting cost. Therefore, on the supply side, the gas-minting segment would be expected to exhibit higher quality, on average, after the treatment. If this holds true, creators would ask for higher prices for gas-minted NFTs, and buyers would be willing to place higher bids on these gas-minted assets. Accordingly, we would expect the gas-minted NFTs to have a higher sale chance and higher selling prices. That is, the quality signaling effect would positively influence matching efficiency for the gas-minting submarket.

Further, the success of the quality signaling mechanism depends upon the existence of a separating equilibrium, whereby creators of low-quality artworks cannot adopt gas minting to falsely signal to buyers that their artworks are of high quality. Such an outcome is possible when buyers do not rely simply on the minting type (chosen by the creator) to determine the value of the NFT. Rather, they use the minting type of the artwork as the starting point of their search process to reduce search friction and are able to discern between high- and low-quality NFTs once they subsequently inspect the artwork. We thus further establish the existence of the separating equilibrium, which is the foundation of an effective quality signaling mechanism (Spence 1973).

These two competing mechanisms have opposing impacts on matching efficiency, and which effect would dominate is an empirical question. The main results reported in Table 3 suggest that the market thickness effect prevails over the quality signaling effect in the entire market, as reflected by the decrease in the average matching likelihood. In contrast, the quality signaling effect dominates the market thickness effect in the gas-minting segment, as manifested by the increase in matching likelihood and first-sale price. Next, we provide direct empirical evidence on the existence of these two mechanisms and discuss the resultant implications for various stakeholders (i.e., supply side, demand side, and the overall market).

5.1. Market Thickness Effect

Evidence for the Increase in Market Thickness

We first provide model-free evidence at the platform level to demonstrate the increase in market thickness. The results presented in Table 4 illustrate how the introduction of lazy minting affects the average number of NFT supplies and creators per week on Rarible. Consistent with our expectation, there was an influx of market supplies and participants after lazy minting was introduced, with more than 99% of the Rarible NFTs created by lazy minting. To get a better sense of the substantial change in market thickness caused by the lazy-minting policy, we visualize the weekly trends of the total number of creations and creators on each platform in Appendix C.

Next, we provide formal empirical evidence to confirm the increase in market thickness and quantify the market thickness effect. Specifically, we examine how creators respond to lazy minting in terms of their daily number of creations. To do so, we construct a panel dataset at the creator-day level, recording how many artworks each creator created each day. We conduct the following analysis:

$$\textit{Number of Creations}_{kt} = \beta_0 + \beta_1 Post_t \times Treated_k + v_k + u_t + \epsilon_{kt}, \qquad (2)$$

where k denotes the creator, and $Treated_k$ equals 1 if creator k is from Rarible, the treatment platform. $Post_t$ equals 1 if day t is after the treatment. The outcome variable of interest is a count measure, $\textit{Number of Creations}_{kt}$. In this analysis, we add the creator fixed effects v_k and the day fixed effects u_t. ϵ_{kt} is the idiosyncratic error term. We perform this analysis with two different samples, given that the lazy-minting policy is likely to change the creator pool: (1) all of the creators who had created at least one NFT, and (2) the existing creators who had produced NFTs before the treatment.

Table 4. Market Thickness Change on Rarible and Foundation

	Rarible (Treatment Group)				**Foundation (Control Group)**	
	Average No. of Gas-minted NFTs Per Week	Average No. of Lazy-minted NFTs Per Week	Average No. of Creators of Gas-minted NFTs Per Week	Average No. of Creators of Lazy-minted NFTs Per Week	Average No. of NFTs Per Week	Average No. of Creators Per Week
Before Treatment	3,241	0	1,675	0	2,103	799
After Treatment	411	*106,683*	218	*14,327*	1,868	766

The results presented in Column (1) of Table 5 suggest that, overall, the lazy-minting option motivates creators to generate 0.082 more creations each day than they did before. This effect is likely due to two forces: (1) lazy minting attracts lots of new creators (specifically 178,179 new creators = 200,451 – 22,272), and (2) lazy minting enhances those existing creators' productivity. Table 5, Column (2), further confirms the second force: The existing creators on Rarible became more productive by creating 0.029 additional NFTs per day, on average, than they did during the pre-treatment periods. This suggests that the market across the board became more active in creating NFTs after the lazy-minting policy, giving rise to a thicker market.

Table 5. Market Thickness Increases: Artists Create More

	(1)	(2)
Variable	*Number of Creations*	*Number of Creations*
Sample	Full Creator Sample	Existing Creators
$Post_t \times Treated_k$	0.082*** (0.005)	0.029** (0.012)
Creator Fixed Effects	YES	YES
Day Fixed Effects	YES	YES
No. of Observations	29,466,297	3,273,984
No. of Clusters	200,451	22,272
Adjusted R-squared	0.059	0.037

Notes. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. Robust standard errors are clustered at the creator level in parentheses.

Evidence for Supply-side Response to Market Thickness Increase

We conjecture that the sharp increase in NFT supply intensifies creators' price competition, weakening their position of commanding higher prices. That is, thriving in a thicker market with a larger number of competitors becomes more difficult for creators. We identify evidence of fiercer competition from the listing behavior of creators. First, we reuse Specification (1) and replace the dependent variable with the minimum asking price (logarithmic) of each NFT during the first 30 days since its creation (or before its first sale, if any) to represent creators' willingness to accept (WTA) a price.[9] We expect creators to lower their WTA as a response to the intensified competition, to enhance their sale probability. Table 6, Column (1), lends support to this statement, indicating a 72.5% (= $e^{-1.290} - 1$) decrease in creators' WTA.

We next leverage another outcome variable to gauge the level of price competition, i.e., Adjust Asking Prices or Not. It is a dummy variable that indicates whether the creator ever adjusted the asking price of each NFT during the 30-day sale window (or before the first sale, if any). This variable reflects whether creators actively monitor the market dynamics and try to compete with other sellers. Rarible charges an additional listing fee (2.5% service fee) up front at the time of any price adjustment. Given the lower chances of selling an NFT in a competitive market, creators may not be willing to pay such irrecoverable menu costs. Thus, we expect that creators would be less active and less likely to alter their asking prices, knowing that the chance to sell NFTs becomes lower in a more competitive market. Table 6, Column (2), supports our supposition, demonstrating that creators adjust their asking prices less frequently; they would rather keep the first asking price untouched and wait for potential sales than pay more money to adjust the prices.

Our third piece of empirical evidence is that, due to the intensified price competition, creators are more inclined to lower, than to increase, the asking price. We compare each adjusted asking price with its

[9] Creators' asking prices include reserved prices in auctions and buy-now prices in fixed-price sales. We use the minimum asking prices among all of the listed prices, including the adjusted ones.

previous asking price to determine whether the creator increases or reduces the price. We then compute the ratio of markdown adjustments, which is calculated by dividing the number of times a creator reduces asking prices by the total number of price adjustments for each NFT during the 30-day period (or before its first sale, if any). As we expect, Table 6, Column (3), shows that the ratio of markdown adjustments increases by 0.053, which translates to an increased rate of 6.80% (0.053/0.780). This result indicates that creators mark down their asking prices more frequently than before (conditional on a price change), suggesting a higher competition level in a thicker market.

Finally, the intensified competition may not only lead to changes in creators' listing behavior, from the sale-outcome perspective, but also may result in a longer time for NFTs to be sold (measured by the number of days to match since an NFT's creation). Because more competing alternatives are now available in the market, each NFT would get lower market exposure, and, thus, the average number of days taken for creators to wait for a match to occur would be extended. As shown in Table 6, Column (4), for each sold NFT, the number of days to match increases by 25.1% after the lazy-minting policy.

Table 6. Intensified Competition on the Supply Side

	(1)	(2)	(3)	(4)
Variable	*Minimum Asking Price (ln)*	*Adjust Asking Price or Not*	*The Ratio of Markdown Adjustments*	*Number of Days to Match (ln)*
Sample	NFT Sample with Asking Prices	NFT Sample with Asking Prices	NFT Sample with Adjusted Asking Prices	Sold NFT Sample
$Post_t \times Treated_{ij}$	-1.290*** (0.049)	-0.238*** (0.011)	0.053*** (0.012)	0.251*** (0.066)
$Fixed\ Sale_i$	0.539*** (0.037)	-0.061*** (0.005)	0.356*** (0.007)	-0.674*** (0.061)
$NFT\ Type_i$	-0.007 (0.036)	0.040*** (0.005)	-0.023*** (0.006)	0.069*** (0.019)
Platform Fixed Effects	YES	YES	YES	YES
Day Fixed Effects	YES	YES	YES	YES
No. of Observations	1,130,233	1,130,233	142,662	20,182
No. of Clusters	147	147	147	147
Adjusted R-squared	0.033	0.023	0.242	0.075

Notes. $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01. Robust standard errors are clustered at the day level in parentheses. Some NFTs' sale type is the open-bid auction without any asking prices, and we exclude those NFTs in this analysis.

Evidence for Demand-side Response to Market Thickness Increase

In a two-sided market, increased market thickness on the supply side tends to be in tandem with an increase in search friction on the demand side, i.e., more alternative offerings available for buyers to compare and choose from. When this happens, each buyer needs to place more bids to increase the chance of securing a match (Hann and Terwiesch 2003, Li and Netessine 2020). To provide evidence for this, we investigate how buyers change their bidding behavior, as measured by two variables: (1) total number of bids placed each week,[10] and (2) average number of bids placed each week to achieve one match, calculated

[10] We mark the number of bids as zero if a buyer/bidder did not place any bids in one week.

by $\frac{Total\ Nubmer\ of\ Bids\ Placed}{Total\ Nubmer\ of\ Matches\ Received}$. We conduct the analysis at the week level rather than at the day level to smooth the sparse bidding activities. For the second measure, we remove the zero-bid observations and focus only on observations with at least one bid placed in one week (i.e., the numerator is at least 1).[11] As a result, we build a panel dataset at the buyer-week level and apply Specification (3) for the analysis:

$$log(Y_{bt}) = \beta_0 + \beta_1 Post_t \times Treated_b + v_b + u_t + \epsilon_{bt}, \tag{3}$$

where b denotes the buyer, and t indexes the bidding week. $Treated_b$ equals 1 if buyer b is from Rarible, the treatment platform. $Post_t$ equals 1 if week t is after the treatment. To make the analysis consistent, we count only the bids placed within 30 days following the creation of each NFT (or before the first sale, if any). We also add the buyer fixed effects v_b and the time fixed effects u_t. For the second outcome variable, if the denominator is 0 at the week level (i.e., no matches occurred), we let the fraction equal the total number of bids placed.[12] Then, to make a clear distinction between the cases of no match and the cases of one match, we control for a dummy variable $Match_{bt}$ in Specification (3), indicating whether buyer b received at least one match from the bids placed in week t (i.e., whether the denominator is greater than 0 or equal to 0). The results in Table 7 suggest that, after the lazy-minting policy, buyers generally tend to place 8.20% more bids (Column 1). Further, as a result of higher search friction, buyers need to place 33.5% more bids, on average, to secure a match in this thicker market (Column 2).[13]

Table 7. Larger Search Friction on the Demand Side

	(1)	(2)
Variable	*Number of Bids (ln)*	*Number of Bids Per Match (ln)*
Sample	Buyer-Week Panel	Active Bidding Panel
$Post_t \times Treated_b$	0.082*** (0.003)	0.335*** (0.072)
$Match_{bt}$	-	0.191*** (0.014)
Buyer Fixed Effects	YES	YES
Week Fixed Effects	YES	YES
No. of Observations	281,086	8,883
No. of Clusters	10,811	2,608
Adjusted R-squared	0.118	0.328

Notes. *p<0.1, **p<0.05, ***p<0.01. Robust standard errors are clustered at the buyer level in parentheses.

5.2. Quality Signaling Effect

To provide evidence that gas minting indeed serves its quality-signaling purpose, we collect evidence to show that the gas-minting segment behaves differently from the entire market in three respects.

[11] We remove the zero-bid sample to ensure that buyers are, indeed, searching for potential matches actively.
[12] We also conduct a robustness check by dropping those observations for which the denominator is 0; the results are consistent.
[13] In addition to the number of bids and the number of bids per match, we conduct a robustness check by changing the outcome variables to (1) total number of unique NFTs that a buyer bids on and (2) average number of NFTs that a buyer bids on per match. As expected, the results are consistent with those in Table 7.

First, on the supply side, creators would use gas minting only when they are confident in the quality of their NFTs and believe that their NFTs could be sold eventually. As a result, gas minting can serve as a credible quality signal because gas-minted NFTs should demonstrate a higher level of quality than do average NFTs in the entire market. In addition, creators also would place higher valuations on the gas-minted NFTs due to the overall higher NFT quality, as manifested by asking for higher prices in the gas-minting segment compared to the entire market. Second, on the demand side, buyers should be able to appreciate the quality signal by showing higher valuations (i.e., higher bids) on gas-minted NFTs than average NFTs in the entire market. In addition, the quality signaling effect of the gas-minting segment may serve as an effective search filter for buyers to better target high-quality NFTs and, thus, reduce the search friction for buyers. Third, once the supply side and the demand side agree on this quality signal when trading, the signaling advantage of gas minting might carry over into the sold/matched NFT segment, which should be the segment of most interest to the NFT platform. In other words, we should also expect the sold gas-minted NFTs to exhibit better market outcomes than sold average NFTs.

Evidence for Quality Signal from Supply-Side Self-Selection into Gas Minting

We argue that, if the quality signal is truly at play, creators would strategically mint high-quality NFTs by gas minting and low-quality NFTs by lazy minting, thus forming a two-tier market segmentation. In the pre-treatment period, the gas-minting segment contains NFTs of both low and high quality, as gas minting was the only option. As a result, we expect the quality of the gas-minting segment to increase after the lazy-minting policy, whereas the quality of the entire market would decrease due to the sheer number of low-quality NFTs from lazy minting.

Unlike physical assets and products, there is a lack of a standard way to measure the quality of a digital asset such as an NFT. We herein come up with three new measures to proxy an NFT's quality: (1) number of *likes* received per day, (2) *willingness to accept* (WTA, as noted above), measured as the minimum asking price set by the seller, and (3) *price markdowns* that captures to what extent the seller is willing to lower the price. The first measure reflects buyers' valuations of the NFT, while the other two reflect sellers' valuations.

First, we use the average number of likes per day as the quality proxy, computed by $\frac{Final\_Likes}{Tenure}$.[14] Normalizing the number of likes (into a daily measure) is necessary because NFTs created at different times have various time windows to accrue likes. The number of likes (e.g., Facebook likes) is documented as an effective and widely used indicator of product quality in online retailing (Li and Wu 2018). Therefore,

[14] NFT tenure is defined by how many days have elapsed since the creation day to February 7, 2022 (i.e., the end of our sample period). This computation entails an underlying assumption that the arrival rates of likes is generally linear over time. We verify that this is truly the case by checking the arrival distribution of new likes across time.

taking the number of likes per day as the dependent variable, we rerun Specification (1) under the full sample and gas-minting subsample to examine how NFT quality changes in different market segments. Table 8, Column (1), shows that the introduction of lazy minting decreases the average NFT quality by 0.032 likes per day (which corresponds to a 0.032/0.050 = 64.0% decrease in quality). In contrast, Table 8, Column (2), shows that there is a significant increase in the number of likes of the gas-minting segment (which corresponds to a 0.050/0.050 = 100.0% increase). A comparison of Column (1) with Column (2), which shows the opposite directions of the NFT quality change, supports our argument that the gas-minting option serves as a valid quality signal and is leveraged by creators who sell high-quality NFTs.

As a natural consequence of the differentiated quality of NFTs, creators should also ask for different prices in the two market segments. We posit that the gas-minting segment would attract high-quality creators who have higher valuations on their NFTs and, thus, demand higher sale prices. In contrast, the lazy-minting segment would attract a large number of low-valuation creators who are willing to sell their artworks at lower prices. In our second measure, we employ creators' WTA, measured by the logged minimum asking price, to gauge creators' valuation and compare the differences between the gas-minting segment and the entire market. The results in Table 8, Columns (3) and (4), confirm our expectations. We observe a striking contrast in creators' WTA: Creators lower their WTA in the entire market by 72.5% ($e^{-1.290}$ – 1), whereas they do not alter their WTA in the gas-minting segment (with a positive but non-significant coefficient).

Table 8. Supply-Side Self-Selection into Gas Minting

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	*Number of Likes Per Day*		*Minimum Asking Price (ln)*		*The Ratio of Markdown Adjustments*	
Sample	Full NFT Sample	Gas-Minted NFT Sample	Full NFT Sample with Asking Prices	Gas-Minted NFT Sample with Asking Prices	Full NFT Sample with Adjusted Asking Prices	Gas-Minted NFT Sample with Adjusted Asking Prices
$Post_t \times Treated_{ij}$	-0.032***	0.050***	-1.290***	0.063	0.053***	-0.218***
	(0.002)	(0.008)	(0.049)	(0.078)	(0.012)	(0.039)
$Fixed\ Sale_i$	0.001	0.057***	0.539***	0.440***	0.356***	0.209***
	(0.001)	(0.003)	(0.037)	(0.050)	(0.007)	(0.015)
$NFT\ Type_i$	0.014***	0.029***	-0.007	-0.127***	-0.023***	0.002
	(0.001)	(0.002)	(0.036)	(0.023)	(0.006)	(0.007)
Platform Fixed Effects	YES	YES	YES	YES	YES	YES
Day Fixed Effects	YES	YES	YES	YES	YES	YES
No. of Observations	1,355,640	75,444	1,130,233	59,010	142,662	14,463
No. of Clusters	147	147	147	147	147	147
Adjusted R-squared	0.003	0.096	0.033	0.079	0.242	0.092

Notes. *p<0.1, **p<0.05, ***p<0.01. Robust standard errors are clustered at the day level in parentheses.

Along the same line, we argue that creators would be less likely to mark down their prices when they make a price adjustment for their gas-minted NFTs due to their high valuations. Hence, we construct our third measure as the ratio of markdown price adjustments. As seen in Table 8, Columns (5) and (6), creators are 27.9% (0.218/0.780) less likely to make markdown adjustments for gas-minted NFTs (in other words, they are more likely to raise their asking prices for this niche gas-minting submarket). In contrast, creators tend to lower their NFTs' listing prices in the entire market due to the predominant competition effect. Taken together, this set of results indicates that creators understand and leverage the quality signals of gas-minting, thus strategically self-selecting gas minting for higher-quality NFTs with higher valuations.

Evidence for Quality Signal from Demand-Side Valuation of Gas Minting

On the demand side, we posit that buyers would appreciate the gas-minting signal because the two-tier market segmentation helps them to conduct quality screening more efficiently and better distinguish high-quality artworks from low-quality ones. Consequently, buyers are expected to exhibit a stronger preference for the NFTs in the gas-minting segment after the lazy-minting policy creates the market tier. We use the highest/maximum bidding price to capture buyers' willingness to pay (WTP) for each NFT. We rerun Specification (1) and report the results in Table 9, Columns (1) and (2). As seen in the table, buyers do not change their WTP significantly in the entire market but significantly raise their WTP on the gas-minting segment, by 198.1%. This finding provides evidence that buyers can discern the quality signal embedded in gas minting and are willing to pay more to purchase a gas-minted NFT.

Table 9. Demand-Side Appreciation of Gas Minting

	(1)	(2)	(3)	(4)
Variable	*Maximum Bidding Price (ln)*		*Number of Bids (ln)*	
Sample	Full NFT Sample with At Least One Bid	Gas-minted NFT Sample with At Least One Bid	Buyer-Week Panel	Buyer-Week Panel, Bids on Gas-minted NFTs
$Post_t \times Treated_{ij}$	-0.093 (0.133)	1.981*** (0.252)	0.082*** (0.003)	-0.032*** (0.006)
$Fixed\ Sale_i$	-1.306*** (0.097)	-1.319*** (0.162)	-	-
$NFT\ Type_i$	0.171*** (0.027)	0.112*** (0.023)	-	-
Platform Fixed Effects	YES	YES	NO	NO
Day Fixed Effects	YES	YES	NO	NO
Buyer Fixed Effects	NO	NO	YES	YES
Week Fixed Effects	NO	NO	YES	YES
No. of Observations	20,977	16,920	281,086	230,750
No. of Clusters	147	147	10,811	8,875
Adjusted R-squared	0.743	0.670	0.118	0.138

Notes. $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01. Robust standard errors are clustered at the day level in parentheses for Columns (1) and (2) and the buyer level in parentheses for Columns (3) and (4).

Further, we expect that buyers' search costs would be significantly reduced in the gas-minting segment, given that the quality signaling mechanism could enable buyers to better distinguish and target high-quality NFTs for purchase, leading to a more efficient and less costly search process in the gas-minting segment. To test this, we recount the number of bids placed by each buyer, particularly on those gas-minted NFTs, and rerun Specification (3). As seen in Table 9, Column (4), buyers, on average, bid 3.20% fewer bids on gas-minted NFTs after the lazy-minting policy, suggesting a significant reduction in search friction for buyers who look for NFTs in the gas-minting segment. In contrast, buyers experience intensified search friction in the overall market due to the large number of lazy-minted NFTs, as shown in Table 9, Column (3).[15]

Evidence for the Separating Equilibrium: A Necessary Condition for Valid Quality Signals

One prerequisite for a valid quality signal is that no one has the incentive to fake quality type. That is, the signal should truly reveal the sender's quality type, and the signal observers can "separate" high-quality from low-quality actors based on the observable signal, resulting in a valid separating equilibrium (Spence 1973). In our context, if gas minting can serve as a valid quality signal and a separating equilibrium exists, buyers are expected to be able to see through the mimicking behavior of low-quality creators who adopt gas minting to imitate high-quality ones. If this is indeed the case, low-quality creators should see no improvement in matching outcomes when leveraging gas minting, so they would not have an incentive to choose gas minting and pretend to be of high quality. In other words, the gas-minting quality signal would work only for high-quality NFTs created by high-quality creators but not for low-quality NFTs created by low-quality creators, thereby disincentivizing low-quality creators to use gas minting and separating the two segments of creators.

To support the above arguments, we test for the presence of the underlying separating equilibrium of the gas-minting signal. We first define the quality type of an NFT creator. We focus on the existing creators who created NFTs before the lazy-minting policy and determine each creator's quality type based on his or her past selling experiences. Specifically, we count the total number of NFTs that a creator sold before the lazy-minting policy. We find that 61% of the creators never sold any of their artworks (i.e., no selling experience), and we define these creators and their NFTs as a low-quality type. In contrast, the top 25% of creators sold at least four of their artworks before the lazy-minting policy, and we regard them and their NFTs as a high-quality type.[16]

Next, we conduct our analysis using Specification (1) within the gas-minting sample, which is further split into two subsamples based on the two quality types. The outcome variables of interest are matching likelihood and first-sale price. We examine whether and how the signal of gas minting works differently for NFTs and creators of differentiated quality. We add creator-fixed effects in this analysis to control for the time-invariant characteristics of creators.

The results are presented in Table 10. We find that low-quality creators do not reap a significantly higher matching likelihood or higher sale prices even when using gas minting after the policy change,

[15] A similar pattern is observed when we examine: (1) number of bids per match and (2) number of NFTs that a buyer bids on, which are the dependent variables we used in Table 7.

[16] We also vary the cutoffs for determining the high-quality type (i.e., three selling experiences, top 20% with six selling experiences, and top 10% with 19 selling experiences), and all the results are consistent.

whereas high-quality creators can sell their artworks more easily (with a 0.145 increase in matching likelihood) at higher prices (with a 37.0% increase in first-sale price) through leveraging gas minting. The findings suggest that the gas-minting signal is effective for only high-quality creators and that low-quality creators are not able to deceive buyers simply by adopting gas minting. Considering the high costs of sending the signal of gas minting (albeit without a significant increase in returns), we expect that rational low-quality creators do not have an incentive to self-select into the gas-minting segment in the long term, whereas high-quality creators do, thus forming a tiered market structure with separating equilibrium. This result echoes the advertising literature, that high-quality sellers are more likely to make upfront investments in advertising to signal their quality, whereas low-quality sellers do not adopt this "money-burning" strategy because their future incomes would not be able to cover the upfront advertising expenditure (Nelson 1974, Kirmani and Rao 2000, Joshi and Musalem 2021).

Table 10. The Separating Equilibrium: The Heterogeneous Effects of Gas-Minting Signal on Low-Quality Creators and High-Quality Creators

	(1)	(2)	(3)	(4)
Quality Type	*Low-Quality Existing Creators*		*High-Quality Existing Creators*	
Variable	*Matching Likelihood*	*First-Sale Price (ln)*	*Matching Likelihood*	*First-Sale Price (ln)*
Sample	Gas-minted NFT Sample		Gas-minted NFT Sample	
$Post_t \times Treated_{ij}$	0.013 (0.019)	0.161 (0.136)	0.145*** (0.043)	0.370** (0.154)
$Fixed\ Sale_i$	0.031*** (0.007)	0.117 (0.084)	0.380*** (0.032)	0.002 (0.044)
$NFT\ Type_i$	0.012 (0.010)	0.122** (0.054)	0.066*** (0.015)	0.120*** (0.029)
Creator Fixed Effects	YES	YES	YES	YES
Day Fixed Effects	YES	YES	YES	YES
No. of Observations	20,562	1,497	16,485	7,919
No. of Clusters	147	141	147	147
Adjusted R-squared	0.465	0.824	0.397	0.783

Notes. *p<0.1, **p<0.05, ***p<0.01. Robust standard errors are clustered at the day level in parentheses.

6. Robustness Checks

We carry out a series of robustness checks that pertain to (1) identification of the impacts of the lazy-minting policy and (2) sensitivity of our econometric analyses. For reference, we summarize these analyses in Table 11. The findings of these robustness checks are consistent with the main results, suggesting that our main results are unlikely to be biased. We omit the details of these robustness checks due to the page limitation.

Table 11. Summary of the Robustness Checks

Category	Concerns	Solutions	Assumption/Target
Identification	Foundation and Rarible might attract different creators and NFTs	Use coarsened exact matching to create a matched NFT sample	To resolve self-selection and make NFTs more comparable
	Unobserved confounding events before the policy change may pollute the	(1) Conduct the placebo test by assigning three fake	To test the no-anticipation assumption

	identification, e.g., users' anticipations of the policy change	treatments; (2) remove the last month's data right before the policy	
	The two-way fixed effects DID model might not be adequate to identify the treatment effect precisely when the effects are heterogeneous	Use a nascent heterogeneity-robust DID estimator (DID_M) developed by De Chaisemartin and D'Haultfoeuille (2020)	To relax the homogeneity treatment assumption and test the parallel-trends assumption
	Unobserved confounding events after the policy change may lead to the observed results	(1) Shorten the post-treatment periods; (2) further employ DID_M	To rule out confounding events after the policy change
	DID estimation with covariates might have model misspecification problems (Sant'Anna and Zhao 2020)	(1) Remove the two covariates from the specifications; (2) use the doubly robust DID estimator	To test homogeneity treatment assumption in covariates and resolve model misspecification
	The serial correlation in the outcome variable may lead to inconsistent and biased standard errors	Employ the random implementation test to shuffle the treatment indicator for 1,000 replications	To show that our results are not driven by false significance that results from serial correlations
Sensitivity analyses	The time window to identify the first sale (i.e., 30 days) might seem arbitrary	Experiment with three alternative sale time windows of 14 days, 60 days, and no restrictions	To show that our results are not sensitive to specific models or parameter selections
	The linear probability model may not be the most proper model for the outcome variable, matching likelihood	Employ the logit and probit models to show the robustness of the main results	To show that our results are not sensitive to specific models or parameter selections
	The first-sale price of lazy-minted NFTs may not be comparable with that of gas-minted NFTs, due to the waived upfront gas costs	For each sold gas-minted NFT, adjust its first-sale price by deducting its upfront gas-minting fee from the first-sale price	To show that our results are not sensitive to specific models or parameter selections

7. Discussion and Conclusion

7.1. Lazy Minting and Platform-level Performance

We have shown how the introduction of lazy minting influences different NFT segments differently. We then take the platform as the stakeholder and examine whether the new policy benefits the platform in terms of the total number of sales and revenues. This is equivalent to investigating whether the efficiency gain from the gas-minting segment recoups the efficiency loss from the lazy-minting segment. Although the presence of the lazy minting option lowers the average matching likelihood, the platform may still benefit from the policy due to the larger market base brought by lazy minting. In addition, the platform may reap higher revenues due to higher sale prices and improved matching efficiency in the gas-minting segment. To provide evidence for these conjectures, we aggregate the data to a platform-day level panel across 147 days and investigate the impact of the lazy-minting policy on the overall platform matching performance, using the following specification:

$$Y_{jt} = \beta_0 + \beta_1 Post_t \times Treated_j + v_j + u_t + \epsilon_{jt}, \tag{4}$$

where Y_{jt} represents the platform-level performance, including the matching ratio, total number of matches/sales, and total commission revenue, calculated by the commission fees received from the first sales of all the NFTs created in day *t* on platform *j*, restricted to a future 30-day sale time window until day *t*+30. We retain the platform fixed effects v_j and day fixed effects u_t in the model.

The results presented in Table 12 suggest that, although the matching ratio decreases (Column (1)), the Rarible platform actually receives 14.266 more successful matches per day (which corresponds to a 14.266/35.429 = 40.3% increase) and 48.8% higher commission revenue after introducing the lazy-minting policy (Columns (2) and (3)). These findings show that it is indeed profitable for platforms to grow the market by leveraging the lazy-minting policy. Although a higher percentage of NFTs cannot be sold, the absolute number of sales and total revenues actually increase.[17]

Table 12. The Treatment Effect of Lazy-Minting Policy on Platform Performance

	(1)	(2)	(3)
Variable	*Matching Ratio*	*Total Number of Matches*	*Revenue (ln)*
Sample	Platform-Level Panel	Platform-Level Panel	Platform-Level Panel
$Post_t \times Treated_j$	-0.038*** (0.009)	14.266*** (5.425)	0.488*** (0.178)
Platform Fixed Effects	YES	YES	YES
Day Fixed Effects	YES	YES	YES
No. of Observations	294	294	294
No. of Clusters	147	147	147
Adjusted R-squared	0.951	0.780	0.787

Notes. *p<0.1, **p<0.05, ***p<0.01. Robust standard errors are clustered at the day level in parentheses.

7.2. Theoretical Implications

Through an opt-in quality-signaling design, we study a new market growth strategy that can preserve matching efficiency while growing markets. To the best of our knowledge, this is the first study that explicitly connects market-entry mechanisms with a quality-signaling design. Although an extensive body of research has examined various quality signals (Kirmani and Rao 2000, Dimoka et al. 2012, Horton et al. 2021), little is known about the role of quality signaling in sparking and sustaining the growth of platforms. Our study thus contributes to the current knowledge by connecting the two streams of literature on market growth and quality signaling, demonstrating the efficacy of quality signaling in ensuring

[17] We also find support for the parallel-trends assumption for this analysis. The results are robust when we identify sales by alternative sale time windows (i.e., 14 days, 60 days, and no restrictions; results available upon request).

matching efficiency while enlarging the market size. Many online markets allow their suppliers to optionally adopt features such as free shipping, free returns, warranties to consumers, and so forth. These features allow suppliers to differentiate themselves from their competitors. The implications of these features, however, in serving as a good quality signal toward growing the platform's market size are not well understood. In this sense, our findings highlight the potential value of optional quality-signaling features designed for suppliers that can aid in rapid market scaling for platforms.

Further, our findings suggest that a thicker and denser market does not automatically degrade matching efficiency, which stands in contrast to the previous literature that typically documents that market thickness hurts matching efficiency due to accentuated search frictions and choice overload (Roth 2008, Geva et al. 2019, Li and Netessine 2020). In the paper most related to our work, Geva et al. (2019) study a platform entry problem and find that the inflow of low-quality campaigns significantly increases market thickness, which reduces individual campaign performance. Our finding that high matching efficiency can co-exist with market thickness, as shown in the gas-minting segment of the NFT market, is in contrast to the conventional wisdom that market thickness and congestion typically lead to deteriorated matching outcomes (Boudreau 2012, Geva et al. 2019, Li and Netessine 2020).

Finally, our study contributes to the signaling literature by empirically establishing the existence of the separating equilibrium (Horton et al. 2021). Signaling-theory studies have examined a variety of quality signals, albeit with little attention to how signals might create separating equilibrium (Bergh et al. 2014), or they predominantly rely on abstract analytical models to build separating equilibrium without much empirical evidence to show its actual presence (Zhang et al. 2022). Our study addresses this gap in the literature by building on the critical concept of separating equilibrium in the signaling literature and empirically proving its presence. Our analysis presents a research opportunity for future studies to empirically validate the separating equilibrium using observational or experimental data.

7.3. Managerial Implications

The new market growth strategy presented in this paper may be a preferable solution to various two-sided platforms that attempt to scale up market sizes. For example, e-commerce platforms can allow third-party sellers to enter freely without setting any requirements to increase market size and, at the same time, allow sellers to determine whether to offer premium services (e.g., free shipping; hassle-free return; qualified certifications, such as Amazon's prime seller badge) as credible quality signals. Similar practices can be applied to online labor platforms (e.g., all workers can enter freely but may self-select to pay a platform premium fee to indicate high working capability), online dating platforms (e.g., self-select to get identities verified), and user-generated content platforms (e.g., self-select to pay an upgrade fee to get higher exposure of contents), among others. In addition, compared to existing matching-enhancing methods (e.g., product reviews; recommendation systems; quality certificates), the opt-in quality signaling design, imposed on the supply side, can be more viable for emerging platforms that face the cold-start problem of short histories, or specific platforms that sell unique and tailor-made products or services (e.g., art markets). Overall, our paper offers insight into solving a common dilemma for different types of two-sided platforms.

For sellers, we show the power of quality signaling in creating market segments and facilitating matches. This provides implications for sellers on how they can survive in a crowded market. High-quality sellers, to achieve better market performance, should strive to improve their quality and then highlight (signal) their quality. For low-quality sellers, it is best not to mimic high-quality users' behavior by adopting the quality signal because, in a tiered market with an established separating equilibrium, this mimicking behavior would not work.

Finally, our paper implies that buyers can rely on the tiered market segmentation formed by the quality signaling mechanism to search for their desired products. Specifically, buyers who care about quality should focus on the high-end seller segment that signals high quality by incurring an upfront cost before earning any revenue.

7.4. Concluding Remarks

A pitfall of the widely believed GBF strategy for growing platform markets is that the strategy may compromise matching efficiency and undermine the quality of markets. In this paper, we identify and investigate a new market growth strategy in the NFT market, namely the lazy-minting policy, which ameliorates the GBF strategy by killing two birds with one stone: growing the market scale while maintaining matching efficiency. We unravel two competing mechanisms of the new growth strategy, i.e., market thickness effect and quality signaling effect, and leverage the policy change of lazy minting in a leading NFT marketplace—Rarible. We find that, although the introduction of the lazy-minting policy decreases the average matching likelihood (attributed to the predominance of the market thickness effect), it benefits the gas-minting segment with improved market quality, higher matching likelihood, and higher sale prices (attributed to the prevailing effect of quality signaling by adopting gas minting). Moreover, we find that the opt-in quality signaling design helps the market to separate creators of differentiated quality and, thus, establishes a tiered market equilibrium by showing that the gas-minting signal works for high-quality creators but not for low-quality creators. Overall, the efficiency gain from quality signaling surpasses the efficiency loss from market thickness, improving overall market performance by increasing the total number of transactions and revenues. As such, our study proves the effectiveness of the new market growth strategy and provides several theoretical and practical implications.

This study provides avenues for future research. First, the measurement of NFT quality (the number of likes per day) may need to be further improved. As the quality of each artwork can be subjective, and the evaluation usually involves potential information asymmetries between NFT creators and researchers, labeling each artwork as high quality or low quality is not a doable task and, thus, is beyond the scope of our study. To achieve a more precise measure of quality, we advocate that NFT markets can provide a public standard to evaluate each NFT's quality (e.g., the rarity and scarcity of NFTs) or create opportunities for NFT creators to publicly assess each other's NFT quality and disclose these data on quality for future research. Second, the new market growth strategy, i.e., the lazy-minting policy, also may have impacts on the secondary resale market. Future research can examine how lazy minting affects product resales for buyers and whether the quality signaling effect still plays a significant role during resales in the secondary market. Finally, although this study focuses mainly on platform-level designs and market-level matching outcomes, it can be extended to investigate the impacts on the behaviors of individual creators or buyers.

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Appendix A: NFT Marketplace Ranking

Figure A1 reports the ranking of Ethereum NFT markets from Dappradar.com, which is one of the most well-known websites for NFT discovery, statistics tracking, and NFT ranking. As we can see from Figure A1, Foundation is the most similar platform to Rarible, with regard to their market share and the number of active trader accounts. This ranking statistic is one reason for us to choose the Foundation platform as the control group. The other reason is that Foundation kept using gas minting during our whole observation period, enabling it to serve as a clean control group in the DID estimation.

#	Market	Avg. price	Traders	Volume
1	OpenSea	$192.23 -14.62%	357,691 -4.45%	$315.77M -16.73%
2	X2Y2 ETH	$248.41 -2.97%	57,602 20.45%	$72.39M 5.85%
3	Element	- -100%	9,653 -5.39%	- -100%
4	LooksRare ETH	$1k -23.35%	6,583 1.48%	$11.09M -35.6%
5	The Sandbox Marketplace ETH	$14.04 -43.87%	3,764 -43.08%	$90.25k -75.15%
6	Foundation ETH	$530.69 12.69%	2,224 -13.87%	$1.16M -7.56%
7	Rarible ETH • Tezos	$342.97 -23.49%	1,433 -10.83%	$576.54k -21.82%

(a) NFT Marketplace Ranking by the Number of Traders

#	Market	Avg. price	Traders	Volume
1	OpenSea	$192.23 -14.62%	357,691 -4.45%	$315.77M -16.73%
2	X2Y2 ETH	$248.41 -2.97%	57,602 20.45%	$72.39M 5.85%
3	CryptoPunks ETH	$147.69k 27.72%	169 49.56%	$23.33M 92.2%
4	LooksRare ETH	$1k -23.35%	6,583 1.48%	$11.09M -35.6%
5	Foundation ETH	$530.69 12.69%	2,224 -13.87%	$1.16M -7.56%
6	Rarible ETH • Tezos	$342.97 -23.49%	1,433 -10.83%	$576.54k -21.82%
7	Decentraland ETH • Polygon	$5.88k -22.47%	107 -16.41%	$518.07k -25.02%

(b) NFT Marketplace Ranking by Total Market Volume

Figure A1. NFT Marketplace Ranking from Dappradar.com

Appendix B: Parallel-Trends Assumption and The Relative Time Model

To test the parallel-trends assumption, we modify Specification (1) by replacing the DID interaction term with decomposed weekly time leads and lags (Burtch et al. 2018, Wang and Overby 2022). We create the relative time dummies at the week level rather than the day level to smooth the fluctuations in the NFT markets. Specifically, we decompose the periods in the last five pre-treatment weeks and those in the first five post-treatment weeks into a set of weekly relative time dummies. To cover the entire period, we collapse all the pre-treatment periods from the beginning (i.e., August 16th, 2021) through five weeks prior to the treatment into one dummy Pre_t^{-6} (which subsumes four pre-treatment weeks), and all the post-treatment periods beyond five weeks post-treatment into another dummy $Post_t^6$ (which subsumes seven post-treatment weeks). The underlying working assumption is that the periods five weeks prior to the treatment should not influence the post-treatment results too much, and the periods five weeks after the treatment should have reached a constant and stable treatment effect. We treat Pre_t^{-1} as the reference baseline because we might see an immediate treatment effect in $Post_t^1$. The final form is as follows:

$$Y_{ijt} = \beta_0 + \beta_{-6} Pre_t^{-6} \times Treated_{ij} + \sum_{\tau=-5}^{-2} \beta_\tau \, Pre_t^{\tau} \times Treated_{ij} + \sum_{\tau=1}^{5} \beta_\tau \, Post_t^{\tau} \times Treated_{ij}$$
$$+ \beta_6 \, Post_t^6 \times Treated_{ij} + \beta_7 Fixed\ Sale_i + \beta_8 NFT\ Type_i + v_j + u_t + \epsilon_{ijt}, \qquad \text{(B1)}$$

where τ indexes the week number, Pre_t^{τ} denotes if creation day t is τ weeks prior to the treatment, and $Post_t^{\tau}$ denotes if creation day t is τ weeks after the treatment. $Post_t^6$ is the collapsed time dummy, representing if day t is in the sixth week or any subsequent weeks following the treatment (similar interpretation for Pre_t^{-6}). Accordingly, β_6 estimates the average treatment effect for the last seven weeks in the post-treatment periods.

As shown in Table B1, all the pre-treatment time dummies are statistically insignificant, suggesting no significant pre-treatment difference in matching outcomes between the two platforms, i.e., the two markets exhibited similar fluctuations before lazy minting was introduced. In addition, there is no clear descending or ascending trend as reflected by the coefficients of the pre-treatment relative time dummies. Hence, the parallel-trends assumption holds, and Foundation could serve as a valid control group. Also, using the decomposed week dummies, we can observe consistent treatment effects in the post-treatment periods.

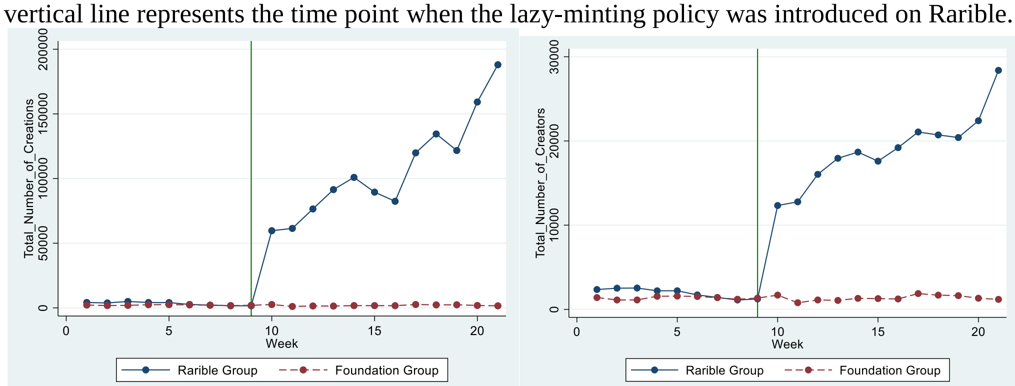
Table B1. Parallel Trends and The Relative Time Model

Variable	*Matching Likelihood*	*First-Sale Price (ln)*	*Matching Likelihood*	*First-Sale Price (ln)*
Sample	Full NFT Sample	Sold NFT Sample	Gas-Minted NFT Sample	Sold Gas-Minted NFT Sample
$Pre_t^{-6} \times Treated_{ij}$	0.006 (0.022)	-0.396 (0.260)	0.019 (0.022)	-0.411 (0.262)
$Pre_t^{-5} \times Treated_{ij}$	0.019 (0.022)	-0.041 (0.392)	0.025 (0.022)	-0.051 (0.396)
$Pre_t^{-4} \times Treated_{ij}$	-0.038 (0.025)	-0.272 (0.309)	-0.040 (0.024)	-0.277 (0.309)
$Pre_t^{-3} \times Treated_{ij}$	-0.014 (0.033)	-0.368 (0.364)	-0.013 (0.033)	-0.381 (0.365)
$Pre_t^{-2} \times Treated_{ij}$	-0.026 (0.026)	0.025 (0.318)	-0.032 (0.025)	0.021 (0.319)
$Pre_t^{-1} \times Treated_{ij}$		*baseline*		
$Post_t^{1} \times Treated_{ij}$	-0.062** (0.025)	-0.668* (0.393)	0.028 (0.023)	-0.338 (0.484)
$Post_t^{2} \times Treated_{ij}$	-0.129*** (0.041)	-0.399 (0.353)	-0.062 (0.060)	0.684 (0.427)
$Post_t^{3} \times Treated_{ij}$	-0.046 (0.029)	-0.666 (0.457)	0.051 (0.034)	-0.354 (0.943)
$Post_t^{4} \times Treated_{ij}$	-0.056** (0.026)	-0.069 (0.399)	0.099*** (0.031)	0.928** (0.388)
$Post_t^{5} \times Treated_{ij}$	-0.046** (0.022)	0.226 (0.414)	0.091** (0.042)	1.544*** (0.314)
$Post_t^{6} \times Treated_{ij}$	-0.020 (0.021)	-0.474* (0.270)	0.121*** (0.023)	1.179*** (0.260)
$Fixed\ Sale_i$	0.006*** (0.001)	0.418*** (0.064)	0.156*** (0.009)	0.362*** (0.066)
$NFT\ Type_i$	0.006*** (0.001)	0.101*** (0.031)	0.033*** (0.005)	0.048* (0.028)
Platform Fixed Effects	YES	YES	YES	YES
Day Fixed Effects	YES	YES	YES	YES
No. of Observations	1,355,640	20,182	75,444	18,679
No. of Clusters	147	147	147	147
Adjusted R-squared	0.302	0.151	0.143	0.140

Notes. $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01. Robust standard errors are clustered at the day level in parentheses.

Appendix C: Market Thickness Change

Note: The vertical line represents the time point when the lazy-minting policy was introduced on Rarible.



(a) Total Number of Creations (b) Total Number of Creators

Figure C1. Market Thickness Change: The Total Number of Creations/Creators by Week