How Free Market Entry Affects Creation and Engagement: Evidence from Non-Fungible Tokens

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Abstract

Content creation costs pose a threat for online marketplaces aiming to attract new users. In response, platform managers devise new policies to subsidize these costs for content creators. In this study, we analyze data from a leading NFT marketplace to examine the impact of a lazy minting policy, which enables content creation without upfront fees, on created content, and engagement with that content. On the creation side, we observe a volume-effort trade-off, with creators producing more work for the market but exerting less effort during creation. On the engagement side, we note a decrease in engagement, particularly affecting creators with higher engagement levels prior to the policy change. We explore the mechanism driving this reduction and find that effort and attention play crucial roles, while a larger follower count does not shield creators from decreased engagement. Finally, we discuss our contributions to the literature and its implications for platform managers.

Keywords: Market design, market entry, non-fungible tokens, lazy minting, digital marketplaces, user-generated content

Introduction

The success of multi-sided platforms relies heavily on their content. Hence, one of the key challenges for platforms is to expand their content supply to stimulate demand (Chu and Manchanda 2016). While previous studies have explored the effects of supply-side growth through platform mergers (Li and Netessine 2020) or less restrictive screening (Geva et al. 2019), the strategy of providing financial subsidies to the supply side has received limited attention. This is surprising given that subsidizing one market side is a common practice in platforms and software markets (Parker and Van Alstyne 2018). Recently, platform's strategy of subsidization has gained renewed relevance with the emergence of platforms that inherently involve costs on the supply side as an integral feature, such as non-fungible token (NFT) platforms. NFTs represent unique blockchain-based digital assets in the form of pictures, GIFs, or videos, and have spawned a burgeoning ecosystem. The creation of NFTs incurs financially costs for creators, as they need to pay a fee (gas fee) to blockchain miners who validate token creation on the blockchain by solving complex computational problems. This context presents a unique opportunity to investigate the following research question:

What are the consequences of financial subsidies to content creators on NFT platforms?

Our econometric analyses focused on the introduction of a "lazy minting" option on the Rarible platform, which led to a sudden reduction in gas fees. This feature was implemented on October 18, 2021 (referred to as "the shock"). Lazy minting enables NFT creators to upload digital assets to the marketplace without immediately minting. The minting process is triggered only when an NFT is purchased, shifting the responsibility of paying the gas fee from the creator to the (first-time) buyer. Consequently, lazy minting reduces the NFT creation cost for creators, who previously had to pay the gas fee before minting.

To address our research question, our primary focus will be on the volume of tokens created, and levels of engagement with these tokens. The direct impact on these outcomes may not be immediately evident, yet understanding these factors is essential for both platforms and scholars.

Regarding token creation, conventional wisdom suggests that reducing costs would lead to an increased volume of creation (i.e., the number of tokens). However, several questions remain. First, will new creations be primarily introduced through the costly (regular) minting process or the free (lazy) minting option? Second, will creators alter the effort they invest in their creations after the introduction of lazy minting? Third, will the increase in new creations and changes in creation effort be driven by existing creators (i.e., users who had created at least one token before lazy minting) or by new creators (i.e., users who entered the market after the introduction of lazy minting)? We address each of these questions in our analyses.

Predicting the outcomes for engagement is even more challenging. On one hand, reducing creation costs may result in an influx of token creations, some of which may stimulate high user engagement. This could have two potential consequences: (1) high-engagement tokens that would not have been minted otherwise may enter the market, and (2) existing creators might be motivated to elevate their effort in crafting high-engagement creations to maintain relevance and ensure the desirability of their newly minted tokens. In this scenario, the average engagement of the created tokens may increase. On the other hand, by reducing barriers to entry, creators seeking quick profits might invest less effort, resulting in low-engagement creations that fail to attract buyers. These creations could include plagiarized or spam tokens[1],[2]. If this scenario unfolds, the average engagement may diminish. Therefore, it remains unclear which effect would prevail.

Our empirical analyses reveal three key findings. First, the volume of tokens created sharply increases after the introduction of the lazy minting policy. However, this increase in token creation is accompanied by a decrease in effort per token, leading to a volume-effort trade-off. This pattern is consistent for both creators who entered before and after the policy change. Second, token engagement, measured by the number of likes received, is reduced for tokens created using lazy minting (referred to as "lazy tokens"), compared to tokens created through regular minting (referred to as "regular tokens"). This decrease in engagement is more pronounced for creators who had high pre-lazy minting engagement, while it is less noticeable for creators with low pre-lazy minting engagement. This pattern suggests a democratization of engagement after the introduction of lazy minting. Third, we examine the reduced engagement and find that it is partially driven by creators' reduced effort in creating tokens and the diminished attention received by lazy tokens. Furthermore, even though a large follower base could potentially shield creators from an engagement decline, our results do not support such a shielding effect.

This research contributes to several streams of literature. First, we contribute to the literature on entry barriers in information goods markets. Prior literature has examined economies of scale or product differentia-

[1] https://twitter.com/opensea/status/1486843204062236676
[2] Such tokens are becoming increasingly easier to locate and remove by the marketplaces.

tion as key barriers to market entry (Bain 1956; Cockburn and MacGarvie 2011; Huang et al. 2013; Karakaya and Stahl 1989; Wen et al. 2016), while our study investigates the effects of reducing marginal product creation costs as a strategy to lower entry barriers. This extends the literature on information goods, which often assumes zero marginal costs, by exploring scenarios where marginal costs are non-zero. Second, we extend the literature on platform scaling (Geva et al. 2019; Li and Netessine 2020; Parker and Van Alstyne 2018; Roth 2008) by examining the side effects, particularly in terms of effort and engagement, resulting from a policy aimed at scaling a platform's supply side. Finally, we add to the emerging literature on the creator economy and NFT marketplaces (Halaburda et al. 2022; Kanellopoulos et al. 2021; Kireyev 2022; Tunc et al. 2022; Zhang et al. 2022). Regarding managerial implications, our findings highlight the need for NFT platforms to carefully consider the advantages and disadvantages of supply-side scaling policies. Additionally, our results underscore the importance of developing new platform design tools to counteract the potential reduction in creator effort and user engagement.

Related Literature

Our work is built upon and contributes to three streams of literature, specifically, on barriers to entry in information goods markets, on platform scaling, and on the creator economy and NFT marketplaces.

Barriers to Entry in Information Goods Markets

In their seminal work on barriers to entry, Bain (1956) identified economies of scale, product differentiation, and absolute cost advantages as significant barriers to market entry. Later, Porter (1980) proposed six barriers to market entry, such as cost advantages of incumbents, product differentiation of incumbents, capital requirements, customer switching costs, access to distribution channels, and government policies. A thorough review of literature conducted by Karakaya and Stahl (1989) identified nineteen different market entry barriers, including seller (market) concentration, sunk costs, and selling expenses. Harrigan (1981) studied entry data across various industries, including aircraft, cement, cigarettes and distilled liquor, and provided statistical evidence that higher entry costs lead to a reduction in the number of firms. Empirical evidence provided by Karakaya and Stahl (1989) suggests that barriers to entry differ between consumer and industrial goods markets. Although our study also examines reducing the barriers to entry in a market, we differentiate ourselves from this literature by focusing on the information goods market, particularly NFT marketplaces, while these papers have mainly concentrated on consumer and industrial goods markets.

Prior literature has investigated the barriers to entry in the information goods markets (Cockburn and MacGarvie 2011; Huang et al. 2013; Wen et al. 2016). Cockburn and MacGarvie (2011) examined the relationship between patents and market entry for new entrants in the software industry. They found that an increase in the number of patents is likely to decrease the number of entrants; however, this negative effect can be mitigated if the entrants have their own patents. Similarly, Huang et al. (2013) studied the entry of independent software vendors (ISVs) to a platform and found that mechanisms that protect ISVs from expropriation, such as a larger stock of intellectual property rights, stronger trademarks, and consulting services capabilities, positively influence the likelihood of joining the platform. In another study, Wen et al. (2016) analyzed the impact of Patent Commons, a practice that reduces barriers to entry for open source software (OSS) community through nonassertion of patents and royalty-free patents, on the entry of new products under an OSS license by software firms. They discovered that lowering barriers to entry stimulated the introduction of new OSS products by entrepreneurial firms. While these studies focused on intellectual property rights and patents as a significant barrier to entry on software markets, our focus is on reducing barriers to entry by enabling cost-free creation in an NFT platform.

Platform Scaling

Platform owners are in charge of a micro-economy and as such, one of their main tasks lies in scaling the platform to maximize revenues (Parker and Van Alstyne 2018). A common strategy has been to scale up the supply side to attract increasing demand, subsequently benefitting from a virtuous cycle between supply and demand due to network effects (Nair et al. 2004). This concept is widely studied in a variety of disciplines. Cennamo and Santalo (2013) investigate two distinct strategies in growing the supply side: (1) growing the number and variety of suppliers and (2) using exclusive contracts with suppliers to prevent supplier multi-homing. They find that combining both strategies leads to worse platform performance than pursuing either one or the other. Chu and Manchanda (2016) investigate the cross-side network effects between the supply and demand side. They find that growing the supply side has stronger positive cross-side network effects on growing the demand side than vice versa. This suggests that the strategy of growing the supply is more important than growing the demand side. Chen and Guo (2022) find that the presence of low-cost advertising (e.g., social media posts) can lead large platforms to open up their supply side to small-scale independent suppliers.

Scaling the supply side of the platform, however, can be plagued with several pitfalls such as congestion (Roth 2008), quality decreases in supply (Geva et al. 2019), and matching inefficiencies (Li and Netessine 2020). Roth (2008) notes that congestion is often a consequence of scaling a platform's supply side. Li and Netessine (2020) investigate this empirically and find that supply-side scaling can decrease matching efficiency and increase search costs on the demand side. Geva et al. (2019) find that platform scaling attempts my decrease the supply-side quality which decreases supply-side performance.

To alleviate such negative side effects, the literature has suggested methods to decrease the information asymmetry between supply and demand side, such as crowd-sourced reviews (Gutt et al. 2019) or manual pre-screening by the platform (Geva et al. 2019). These mechanisms may not lend themselves favorably to any platform, especially not NFT platforms. NFTs do not suffer from classical information asymmetry, hence the usefulness of reviews is very limited. Pre-screening is very time-consuming and it is very difficult if not impossible to clear criteria for pre-screening in artistic domains.

Finally, an alternative approach to platform scaling has been proposed by (Parker and Van Alstyne 2018). They propose cost reductions, i.e., subsidies, to one platform side to maximize overall revenues by collecting higher prices on the other platform side. While this is widespread practice for software products, which partly explains freemium strategies, this is rarely found in two-sided matching platforms. In particular, the costly supply (in the form of upfront payments) of products on platforms is quite rarely observed and the side effects of supply-side subsidies are not yet understood by existing literature. To fill this gap, our study investigates subsidies to the supply side in the form of lazy minting which is added as costs to the demand side.

The Creator Economy and NFT Marketplaces

The rise of financial technologies has led to the development of numerous applications and disrupted traditional markets (Hendershott et al. 2021). Blockchain technology has played a significant role in this disruption, as it reduces the risks associated with incomplete contracts and lowers transaction costs (Haaften-Schick and Whitaker 2022). As a result, artists and other creative workers have increasingly turned to create artwork in the form of NFTs (Kugler 2021). The value of the creative work has appreciated greatly over time. If the artists had retained 10% equity in their work when it was first sold, they would have experienced substantial earnings that would have outperformed the gains in equity markets such as the S&P (Whitaker and Kräussl 2020). Recognizing this value, platforms are shifting their focus toward the creator economy and providing incentives for creators to boost their contributions and attract consumers (Bhargava 2022). For example, some platforms offer revenue-sharing plans to motivate online content producers (Jain and Qian 2021). However, creators may strategically increase or reduce their production of new content in response to these incentive schemes (Jiang et al. 2019). Our research makes a significant contribution to the emerging field by examining how creators alter their creative behavior in response to a platform's newly developed strategy for reducing minting costs.

NFT markets have emerged as a novel type of market that could potentially disrupt other markets (Halaburda et al. 2022). For instance, Kanellopoulos et al. (2021) studied the impact of NFT markets on collectible cards markets and found a significant decrease in prices of physical collectible cards following the introduction of their digital counterparts. However, due to their unique nature, pricing NFTs in these markets can be challenging and subject to various behavioral biases. Kireyev and Lin (2021) examined potential biases in NFT valuations and identified pricing inefficiencies in the market using a structural model. Similarly, Kireyev (2022) investigated how bidding costs affect NFT sales prices and found that lower costs lead to higher sales prices as sellers anticipate more bids. In addition, Tunc et al. (2022) analyzed the impact of resale royalties on NFT sales prices and market liquidity, revealing that these royalties may not always benefit NFT creators or platforms, as they can lead to lower sales prices and impeded market liquidity. Our contribution to this literature is to investigate how reduced minting costs affect the pricing of NFTs when they are listed for sale for the first time.

Our study is closely related to the work of Zhang et al. (2022), which investigates the impact of lazy minting policy in NFT marketplaces with a focus on market matching efficiency. Although we also explore the effects of lazy minting policy, our study differs from theirs in several key ways. In contrast to Zhang et al. (2022), who suggest that lazy minting is a policy towards platform growth that may challenge the effectiveness of matching performance of two-sided markets, we examine whether it leads to an increase in the number of NFTs created within the platform and how it affects the creation behavior of both existing and new creators. Furthermore, while Zhang et al. (2022) argues that creators strategically employ (or refrain from) the lazy minting method to signal quality, we focus on how creators' effort changes when using the lazy minting option and how it reflects on NFT engagement. Therefore, our work not only substantially differentiates from Zhang et al. (2022) but also complements it, providing a more comprehensive understanding of the implications of lazy minting policy in NFT marketplaces.

Background

NFTs have experienced tremendous growth over the past few years. Estimates suggest that the total value of NFT transactions has increased from about 82.5 million USD in 2020 to more than 17 billion USD in 2021[3]. This could be largely attributed to the excessive gains[4] that collectors can experience when they invest in the right assets at the right time. Therefore, NFTs can nowadays be considered investments and they attract both ordinary individuals, investors, as well as celebrities[5].

All this increased popularity has contributed to increased gas fees that creators have to deal with. Since this presents an entry cost of new work to NFT marketplaces, it stands to reason that if it is not dealt with, this could trigger a cascade of negative events: the number of tokens introduced to the market could contract and users would move their attention and their money to other marketplaces, investment options (such as the stock market), or collectibles industries (such as trading card collectibles). To deal with this issue, network operators and NFT marketplaces have undertaken a number of measures. Network operators can scale networks to increase the number of transactions that occur per second. Thus, the networks can become less congested, which will reduce the gas fees. One example of this is the goal of upgrading the Ethereum blockchain. This roadmap includes several upgrades[6] such as "sharding" - a so called "layer 1 solution" - that will allow nodes to process different transactions in parallel with each other[7]. Another example is the layer 2 solutions that are being developed, which attempt to scale the network by offloading part of its work to another layer of the blockchain[8]. Aside from upgrading the existing blockchains, new blockchains have been created altogether that promise much lower gas fees.

NFT marketplaces have also developed solutions aimed at dealing with increased gas fees. The first solution is that they allow NFT creators to introduce a resale royalty on their NFTs. Hence, the creators can yield a reward from each secondary resale of those NFTs. These royalties however need to be adopted with caution, as they can decrease the odds that an NFT will sell and even if they sell they will take longer to do so (Tunc et al. 2022). The second solution is that of introducing lazy minting, which is the focus of our study. Lazy minting allows (token) creators to introduce their (digital) creations into the market without paying a fee. Instead, the digital files are minted only if they are purchased, while the minting fee is borne by the first-time buyers.

Currently, Rarible is one NFT marketplace that allows creators to use lazy minting. Rarible was introduced

[3]https://fortune.com/2022/03/10/bored-apes-cryptopunks-jolt-nft-market-to-billions-in-sales/

[4]https://fortune.com/2022/02/18/how-to-make-money-flipping-nfts-on-open-sea/

[5]https://www.wired.com/story/nft-celebrity-regulation/

[6]https://ethereum.org/en/upgrades/

[7]For more information on sharding we refer the reader to: https://vitalik.ca/general/2021/05/23/scaling.html and https://medium.com/nerd-for-tech/scaling-the-blockchain-layer-1-2-techniques-meet-43f68ee24afa

[8]https://vitalik.ca/general/2021/01/05/rollup.html

in 2020 and within about 18 months it was valued at about US$ 14.2 million[9]. The platform's consistent updates to improve its services[10] have allowed it to rank among one of the major NFT marketplaces[11]. Lazy minting is one of the service improvements that Rarible introduced in October 18, 2021 which we refer to as the "shock date". Before that date, the platform members could only create tokens using regular minting (we name these "regular tokens"), while after that date they could also use lazy minting to create their tokens (we name these "lazy tokens"). In this paper, we categorize (token) creators into either "existing creators" which we define as those users who had created at least one token before the introduction of lazy minting, or "new creators" who are the rest. Therefore, all the tokens that were introduced before the shock date were created by existing creators, while those introduced after the shock date were created either by existing or new creators.

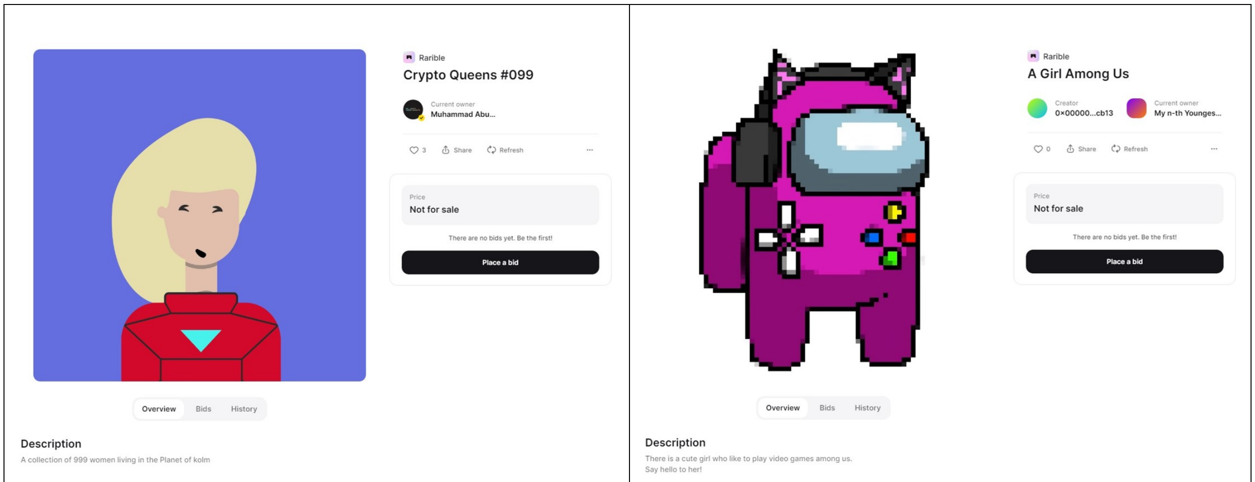
One might think that shifting towards lazy minting is what all creators should do. Although lazy tokens offer the advantage of lower entry costs for creators, they still have a few potential disadvantages that should be considered. First, the minting cost shifts from the creators to the first-time buyers. Thus, if these tokens are (in total) more expensive compared to regular tokens, first-time buyers might lean towards purchasing regular tokens. Second, lazy tokens are not automatically "inserted" on the blockchain. This only happens when these tokens are minted and until then they remain uploaded to the NFT marketplace as digital assets. Tokens that are not on the blockchain are more likely to be affected by copyright issues; these are largely attributed to users copying others' NFTs and uploading them as their own. Major marketplaces are employing teams to deal with these issues and early results seem promising[12], even though they focus only on popular NFT collections - not tokens that do not belong to collections. Third, lazy tokens in one marketplace are only available in that marketplace, unless they are minted. Since they are not available on multiple platforms, they have less exposure to other users, which could negatively affect their first-time sale price. Apart from creator incentives to use lazy minting, one might also think that Rarible itself has the incentive to promote one option of creating tokens over the other. This however is not true, as there are no direct monetary incentives for Rarible to do so; its fees rely solely on token sales[13].

Another thing to note with regard to the two token creation options is that there are no indicators that display or suggest which option was used to create a token. To better understand this, we display two examples of tokens in Figure 1 that follows. The one on the left is an example of a regular token and the one on the right is an example of a lazy token. As we see, the structure of the two token pages is identical to each other and one cannot tell which token creation option was used to create each of the tokens. The only way that users (others than the creators) can reliably tell this is if they download data from the blockchain. Given that this is a highly technical action that users do not need to familiarize themselves with when using NFT marketplaces, we believe that the majority of Rarible's users are not aware of how to distinguish between the two token creation options. As a result, we posit that whether a token is created using regular or lazy minting should have no effect *by itself* on platform members' engagement with that token.

Data and Empirical Strategy

To analyze the impact of lazy minting on the market, we use data from Rarible. When users create a token on Rarible they are asked to assign it to a collection[14]; an irreversible action. Creators are given two collection options: place their token into a default Rarible collection or place it in their own collection(s). The second option is seldom preferred by creators as it incurs further market entry costs associated with creating a collection. For that reason, in our analysis we collect data for the available default Rarible collections; one referring to regular tokens and two others referring to lazy tokens. We collect our data using the API that is available by the platform[15]. Our data includes all the tokens (belonging to either of these collections) that were introduced on Rarible from January 1, 2021 up to March 1, 2022 (about 9 months before and 4 months

[9]https://techcrunch.com/2021/06/23/nft-marketplace-startup-rarible-closes-14-2-million-series-a/
[10]https://rarible.com/blog/rarible-2021-a-year-in-review/
[11]https://dappradar.com/nft/marketplaces
[12]https://twitter.com/opensea/status/1587194630432497664
[13]https://rarible.com/how-it-works/getting-started/what-are-Raribles-fees
[14]https://guide.rarible.com/frequently-asked-questions/collections
[15]Our data collection was completed using the API found in https://ethereum-api.rarible.org/v0.1/doc. In case this link is no longer accessible, we point the interested parties to https://docs.rarible.org/api-reference/ instead.



(a) Token Created Using Regular Minting | **(b) Token Created Using Lazy Minting**

Figure 1. Token Examples

after the shock). In total, we have 126,736 regular tokens and 2,593,064 lazy tokens.

For every token, we have available a variety of information that describes the token and the engagement of Rarible members with the token. With regards to the former, for every token, we obtained the ID of its creator, the creation option under which it was introduced (i.e., regular or lazy minting) into the platform, the date when it was introduced, whether its digital file is a static image without sound, and what royalty rate it has been assigned (if any). By assigning a royalty to a token, its creator will receive a percentage (equal to the royalty rate) of the sale price for any subsequent sales of the token. We also have available the size of the token's digital file, whether the token has any description assigned by its creator, as well as the length of the description (if any) in words. With regards to the engagement metric, for every token, we have available a panel data set of the number of likes it has received - from other members of the platform - from the month it was introduced to the platform up to March 1, 2022. The descriptive statistics of the regular and lazy tokens can be seen in Table 1.

Minting	Variable	N	Mean	S.D.	Min	Max
Regular	Static Image	126, 736	0.738	0.440	0	1
	Royalty Rate	126, 736	12.037	8.100	0	100
	File Size	126, 736	4, 790, 234	9, 211, 080	1	104, 853, 380
	Has Description	126, 736	0.767	0.423	0	1
	Descr. Length (Words)	126, 736	24.124	55.271	0	6, 642
	Received Likes	126, 736	9.669	43.816	0	9, 988
Lazy	Static Image	2, 593, 064	0.921	0.269	0	1
	Royalty Rate	2, 593, 064	10.827	7.785	0	100
	File Size	2, 593, 064	1, 926, 540	6, 363, 664	68	146, 314, 872
	Has Description	2, 593, 064	0.565	0.496	0	1
	Descr. Length (Words)	2, 593, 064	15.107	35.510	0	7, 134
	Received Likes	2, 593, 064	0.970	6.522	0	2, 884

Table 1. Descriptive Statistics

The table contains 6 variables. The first is "Static Image" and we use it to identify the tokens whose digital files are static images without sound. These tokens are assigned the value "1" for this variable. Otherwise, if the digital files contain any form of animation or sound, then their tokens are assigned the value "0" for this variable. One might notice that some tokens have missing values in the variable "Static Image". This is because we were unable to classify whether their digital files are static images without sound using the file type information that was available on the blockchain[16]. The variable "Royalty Rate" shows the tokens' assigned royalty rate. If there is no royalty, then the value is 0. The three variables that follow refer to the tokens' file sizes and descriptions. These variables were extracted from the tokens' meta data and for some tokens their values were unavailable. Lastly, "Received Likes", indicates the total number of likes that tokens have received up to March 1, 2022.

Table 1 allows us to make a number of observations. First, we find that the quantity of lazy tokens vastly exceeds that of regular tokens. Second, the numbers suggest that creators reacted by creating tokens that are more likely to be static images, have smaller file sizes, are less likely to have descriptions, and if they do, they are shorter. Third, in the table, we also see that lazy tokens receive, on average, a much lower number of likes compared to regular tokens. This implies reactions in the engagement levels of Rarible members with the tokens. To better understand how the market reacts to the introduction of lazy minting, we split our analysis into two parts: one referring to reactions from the token creation side and the other referring to the engagement levels of members with the tokens.

Creation

Before introducing our statistical analysis, we check the reaction of the creation side graphically. First, in Figure 2 we investigate the number of (new) tokens that were introduced every week of our observation window for each token creation option. On the left, we have the number of regular tokens introduced per week and we see that they reached a peak about 32 weeks before the shock date. This could be driven by the multi-million dollar sale of NFTs which took place around that time[17]. Afterward, about two thousand new regular tokens were introduced weekly to the platform, while after the shock date this number dropped to less than 50. On the right, we have the number of new lazy tokens introduced per week. The graph has no observations before the shock date, as this option was unavailable then. However, right at its launch, lazy minting became far more popular than regular minting. Indicative of its popularity is that although 126,538 (regular) tokens were created before the shock, this number jumped to 2,593,262 after the shock with 2,593,064 of them being lazy tokens and the rest (198) being regular tokens. Essentially, regular tokens almost completely disappeared from the market. Apart from an increase in new tokens, Rarible received a large influx of new creators after the lazy minting option was introduced, as we can see from Figure 3a.

Results

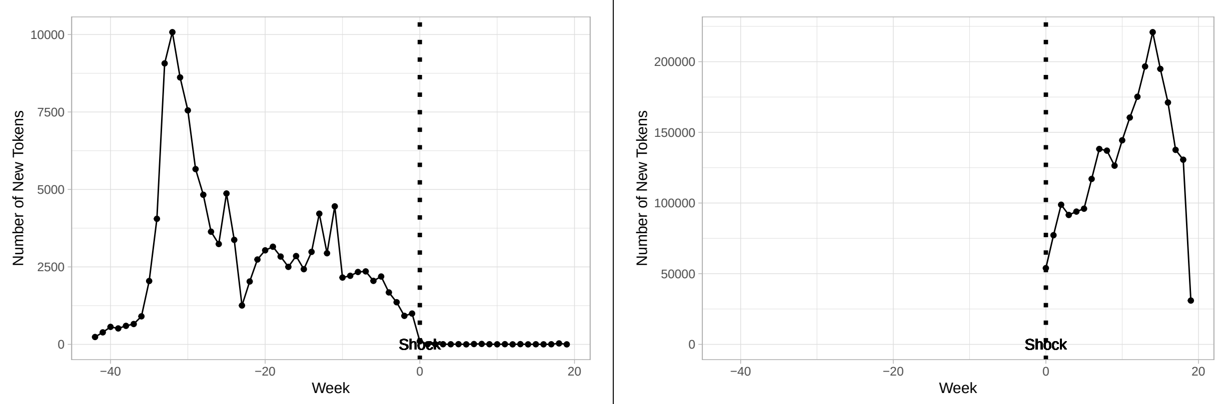
Volume of Tokens

We start our statistical analysis of reactions of the creation side by analyzing the volume of tokens created by users. As we saw from Figure 2, the model-free evidence suggests that users increase the volume of tokens that they create. To gather statistical evidence on whether this is the case we use the following specification:

$$\textit{Cumulative Volume}_{j,t} = \beta_0 + \beta_t \textit{Relative Month}_t + \gamma_j + \epsilon_{j,t} \tag{1}$$

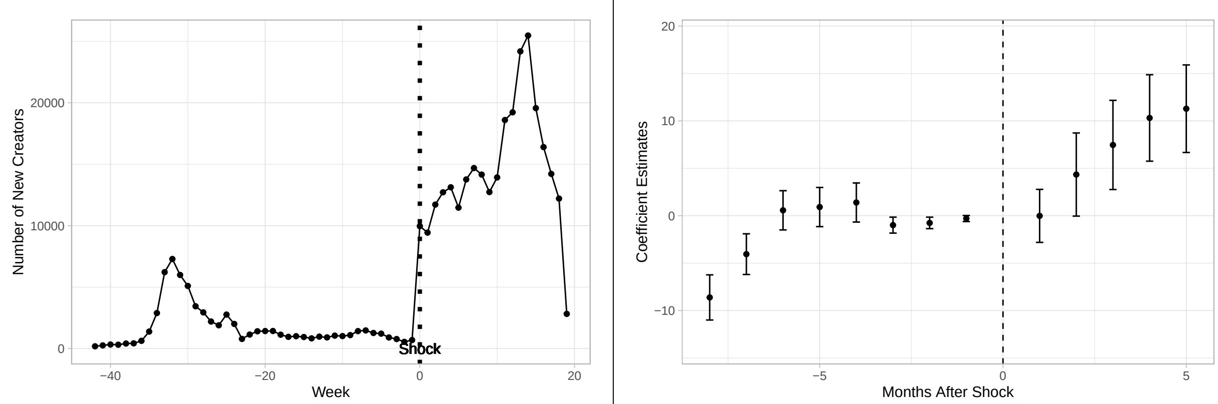
where $\textit{Cumulative Volume}_{jt}$ is the cumulative volume of tokens that user j has created up to period (month-year combination) t, $\textit{Relative Month}_t$ refers to months relative to the treatment date, and γ_j is a vector of creator fixed effects, used to control for unobserved time-invariant differences across creators that could potentially affect token creation. In this specification, we cluster the standard errors at the creator level and we use the month preceding the shock as our baseline. After running the specification, we extract the coefficient estimates and plot them alongside 95% confidence intervals in Figure 3b. The coefficient estimate is positive and constantly increasing for the months after the shock, reaching a peak of about 11.28 in the end of the observation window. This suggests that after the shock users increase the volume of tokens that they create.

[16]The content type of these tokens can include "application/octet-stream", "text/plain", "application/json", "application/pdf", or "image/procreate". We also attempted to classify these tokens through visual inspection but their digital files were inaccessible.
[17]https://onlineonly.christies.com/s/beeple-first-5000-days/beeple-b-1981-1/112924



(a) Regular Tokens | **(b) Lazy Tokens**

Figure 2. Total Number of New Tokens per Week



(a) Total Number of New Creators per Week | **(b) Token Volume**

Figure 3. New Creators and Token Volume

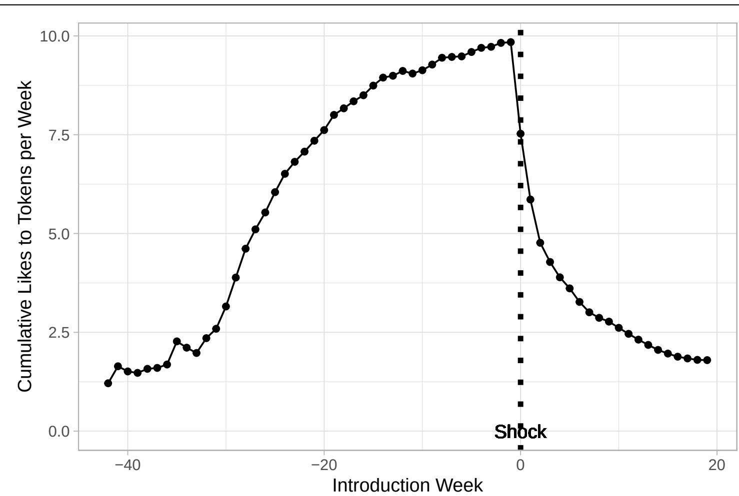


Figure 4. Ratio of the Cumulative Likes Received to the Cumulative Number of Tokens

Effort in Tokens

One might wonder how creators achieve such a big increase in their token output. A reason for this could be that they exert less effort in creating their tokens. To investigate this, we use the following specification:

$$\textit{Effort Proxy}_{i,j,t} = \beta_0 + \beta_1 \textit{Lazy Minted}_i + \gamma_j + \delta_t + \epsilon_{i,j,t} \quad (2)$$

where $\textit{Effort Proxy}_i$ is an effort proxy for token i that we use and $\textit{Lazy Minted}_i$ is a dummy variable indicating whether token i was lazy minted. In addition, γ_j refers to a vector of creator fixed effects and δ_t refers to fixed effects for the year, month, and weekday when token i was introduced to control for temporal effects, while we cluster the standard errors at the creator level. The results of this specification can be seen in Table 2, where we use four different effort proxies. In column (1), we use as proxy whether the token's digital file is a static image without sound. If so, then it can be argued that the creator exerted less effort in their token. In column (2), we use as proxy the size of the token's digital file, as a larger file would indicate a token that required more effort. In column (3), we use a proxy whether the token has a description ("Has Descr."). In column (4), we use as proxy the description length in words ("Descr. (Words)"). It can be argued that tokens that have (do not have) a description and tokens that have longer (shorter) descriptions required more (less) effort to be created. Across all columns, the coefficient estimates indicate that creators exert less effort (as measured by the proxies) for the tokens that they created after the shock. One might argue that these results could be driven by strategic creators, who did not introduce their low-effort work before the introduction of lazy minting due to the high gas fees but did so shortly afterward. To investigate this, we replicate this analysis but exclude the tokens that were introduced within two weeks of the introduction of lazy minting. We use a time window of two weeks, as the NFT industry is evolving rapidly and the multiple radical changes within a wider time window could lead to biased estimates. The coefficient estimates are still significant at the 1% level, indicating that our results are unlikely to be driven by such a strategic behavior.

	Static Image	Log Size	Has Descr.	Descr. (Words)
	(1)	(2)	(3)	(4)
Lazy Minted	0.066^{***}	-0.278^{**}	-0.097^{***}	-0.153^{***}
	(0.017)	(0.111)	(0.020)	(0.047)
Creator Fixed Effects	Yes	Yes	Yes	Yes
Intro Time Fixed Effects	Yes	Yes	Yes	Yes
Has Description Controls	No	No	No	Yes
Adjusted R^2	0.561	0.690	0.778	0.938
Observations	2,719,686	2,194,996	2,719,798	2,719,798

Notes: In all specifications, we cluster the standard errors at the creator level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2. Creation Effort

Taken together, the analyses suggest the presence of a creation-effort trade-off. While creators increase token volume, they decrease their effort on those creations on average.

Existing vs. New Creators

The evidence so far suggests that while creators increased the volume of tokens that they produced, they reduced the effort they exert into their tokens. Nevertheless, it remains unclear which creators drive these effects. In Figure 3a, we saw that after the introduction of lazy minting there was a large influx of new creators. Hence it could be the case that our estimates are driven by these new creators and they are not the result of changes in the behavior of existing creators. We study the two types of creators separately and we discuss our methodology and results below. We are unable to present these results due to space limitations.

We start by turning toward existing creators. First, we study whether they produced a larger number of tokens than they did before the shock. To study this, we run an analysis similar to that of Equation 1 but use only the subsample of tokens that were created by existing creators. The results follow a similar pattern to that of the analysis for all the creators, in that all the estimates for the months after the shock are significant at the 5% level. Second, we study whether they changed the effort they exerted toward token creation after the introduction of lazy minting. We do so using an analysis similar to that of Equation 2 with the only difference being that we analyze only the existing creators. The coefficient estimates are consistent in magnitude and significance with those of the main results, suggesting that existing creators reduce the effort that they exert in their creations.

Next we analyze the tokens of new creators. One way to do so would be to compare the new creators who entered because of lazy minting to those who entered for other reasons. In our setting, however, this is not possible. Since we do not have a treatment and control group, all new creators who entered after the shock could have done so *because* lazy minting was introduced. Thus, we study new creators by comparing new creators who entered the market shortly *after* the shock to new creators who entered shortly *before* the shock. By focusing on a narrow observation period around the shock date, we assume that new creators who entered the market shortly *before* the shock are a comparable control group to new creators who entered the market shortly *after* the shock. Therefore, we use a regression discontinuity identification strategy on the subsample of the tokens of new creators who entered either from October 03, 2021 up to October 17, 2021 (i.e., shortly *before* the shock) – the control group – or from October 18, 2021 up to November 03, 2021 (i.e., shortly *after* the shock) – the treated group. We choose an observation window of two weeks before and two weeks after the shock date for sampling the creators, as the NFT industry is evolving rapidly and the multiple radical changes within a wider time window could lead to biased estimates. Using this strategy allows us to estimate the difference between creators who joined shortly before the shock date and those who joined shortly after – possibly due to the introduction of lazy minting.

To analyze token volume, we estimate Equation 1 and restrict the sample to new creators. The results similar to the estimates for all creators, in that new creators increase their token volume for the months following the shock. Next, we turn to creator effort. For that, we estimate a model similar to that for all creators but it differs in that we analyze only the new creators and we add a binary variable indicating whether a creator entered after the shock ("Creator Entered After Shock"). The results coefficient estimates of "Creator Entered After Shock" are insignificant at the 10% level, suggesting that creators entering before vs after the shock do not differ in the effort they exert when creating their tokens. The coefficient estimates of "Lazy Minted" are consistent in magnitude and significance with those of the main results, suggesting that creators exerted less effort towards lazy tokens, compared to regular tokens.

In summary, our findings indicate that both types of creators respond to the introducing of lazy minting by increasing their token volume, while also exhibiting a creation-effort trade-off.

Engagement

Based on the evidence thus far, it appears that users amplify the volume of tokens that they create following the shock, yet invest less effort in creating lazy tokens. An inevitable question arises: do these shifts carry any consequences for the engagement of platform members with these tokens?

Before presenting our identification strategy, we explore the impact of the lazy minting option using as metric the ratio of total likes received by tokens to the total number of tokens present in the market as our metric. We estimate this metric from the start of our observation window up to every week of our observation window and we plot these numbers in Figure 4. We expect this figure to have a positive slope for the majority of 2021. This is because NFTs became increasingly popular within 2021 which we posit would reflect in a growing number of users becoming engaged with them (i.e., liking tokens). At the same time, the number of tokens would have a lower rate of increase, since the high gas fees would have deterred many users from creating tokens. As a result, the metric we study would be consistently increasing. Nevertheless, we expect this to potentially change after the introduction of lazy minting. This option now allowed users to introduce their tokens into the market for free which as we saw was associated with an influx of new creators (Figure 3a) and tokens (Figure 3b). We expect that this would now affect our metric such that the figure would have a more flat or even negative slope. Indeed, we find that after the introduction of lazy minting there is a sharp decline.

Although suggestive, this model-free evidence does not permit conclusions about whether the introduction of lazy minting affects the token engagement. To achieve that, one must control for several confounding factors related to the metric that we employ, the token supply, the popularity of Rarible, and the broader popularity of NFTs. Furthermore, using panel data instead of cross-sectional data proves advantageous in analyzing the dynamics of a token's likes over time. In this vein, for our identification strategy, we employ the following specification:

$$\textit{Engagement Proxy}_{i,j,t} = \beta_0 + \beta_1 \textit{Lazy Minted}_i + \gamma_j + \delta_t + \epsilon_{i,j,t} \tag{3}$$

where $\textit{Engagement Proxy}_{i,j,t}$ is a logarithmic transformation of the number of likes that token i by creator j received in month t and $\textit{Lazy Minted}_i$ is a dummy indicating whether token i was lazy minted. We control for creator fixed effects, γ_j, and month-fixed effects, δ_t, while we cluster the standard errors at the creator level and the token level.

Results

Main Analysis

The results of this specification can be found in column (1) of Table 3. The coefficient estimate suggests that lazy tokens gather about 15.5% fewer likes. We enrich our specification by adding more control variables and report the updated coefficient estimates in each of the columns that follow. First, we control for two characteristics of each token (column (2)), namely whether its digital file is a static image without sound, and what its royalty rate is and we find that the coefficient estimate is almost identical. Second, we additionally control for the number of days that the token has been available in the platform (column (3)), since tokens that stay longer in the platform have more time to gather likes - which could affect the estimates. We find that the coefficient estimate now changes to a reduction of about 16.8%.

Third, we extend our model (column (4)) by controlling for the supply of tokens in Rarible through two metrics: (1) the number of tokens that were available (in Rarible) in the week that tokeni was introduced in Rarible and (2) the number of tokens that were introduced (in Rarible) in the same week as tokeni. This allows us to control for a potential reduction in the number of the engagement due to larger competition for user attention between tokens. Finally, in column (5), we further control for both the popularity of the platform and for the interest towards digital collectibles. To control for the popularity of the platform, we use the number of active users on Rarible. We control for this because lower platform popularity could affect the tokens' engagement. For the number of active users, we use the number of unique wallets that were active on Rarible[18]. Moreover, in this specification, we also control for the popularity of NFTs, as a reduced interest towards digital collectibles could lead to a reduction in engagement. To control for interest towards digital collectibles, we use the "NFT Global Sales Volume Index" which is available by CryptoSlam[19] - a website that aggregates NFT data from several blockchains. The coefficient estimate of this specification is now a reduction of about 21.4%. We continue our analyses using the last specification since it allows us to control for all the identified potential confounders.

Margin Analysis

In Figure 2, we observed that after the introduction of lazy minting, the vast majority of new tokens were introduced using this new option. In addition, lazy tokens received on average a much lower number of likes (median is 0) as we saw from Table 1. This could mean that the coefficient estimates of our main specification (last specification of Table 3) are driven by these lazy tokens which receive no likes and that have flooded the market, thus diluting the average number of received likes. To investigate this, we borrow from labor economics and rerun our main specification, estimating the coefficients at the extensive and intensive margin (Besedeš and Prusa 2011; Felbermayr and Kohler 2006).

The results are presented in columns (1) and (2) of Table 4. In column (1), we analyze the extensive margin by changing the dependent variable to whether a token has received at least 1 like (in total) up to March 1, 2022 and keeping only one observation per token. In column (2), we analyze the intensive margin by using as a dependent variable the logarithmic transformation of the number of received likes and keeping all the observations for every token but we only analyze those tokens that have received at least one like. In

[18]https://dappradar.com/multichain/marketplaces/rarible
[19]https://www.cryptoslam.io/nftglobal

	Log Received Likes				
	(1)	(2)	(3)	(4)	(5)
Lazy Minted	-0.155^{***}	-0.154^{***}	-0.168^{***}	-0.195^{***}	-0.214^{***}
	(0.019)	(0.019)	(0.020)	(0.022)	(0.023)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Creator Fixed Effects	Yes	Yes	Yes	Yes	Yes
Introduction Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Static Image and Royalty Rate	No	Yes	Yes	Yes	Yes
Days Available	No	No	Yes	Yes	Yes
Token Supply	No	No	No	Yes	Yes
Rarible Popularity	No	No	No	No	Yes
NFT Interest	No	No	No	No	Yes
Adjusted R^2	0.382	0.382	0.382	0.382	0.383
Observations	7,702,877	7,702,485	7,702,485	7,702,485	7,702,485

Notes: In all specifications, we cluster the standard errors at the creator level. *p<0.1; **p<0.05; ***p<0.01

Table 3. Main Effects

both specifications, we control for all our identified confounding factors, while in column (1) we cluster the standard errors at the creator level and in column (2) we cluster the standard errors at the creator level and token level. The insignificant coefficient estimate of column (1) indicates that lazy tokens are not less likely to receive at least one like, compared to regular tokens. Furthermore, the significant coefficient estimate of column (2) indicates that the effect is driven by tokens that have received at least one like.

When considered collectively, the results suggest that the average number of likes received by tokens does not decline due to dilution - that is, a swath of new tokens with zero total likes entering the market. If this were the case, we would anticipate the coefficient in column (1) to be significant. Instead, the decline is primarily driven by lazy tokens receiving fewer total likes compared to regular tokens, suggesting that platform members are less engaged with lazy tokens.

	Total Received Likes	
	Extensive Margin	Intensive Margin
	(1)	(2)
Lazy Minted	-0.044	-0.248^{***}
	(0.039)	(0.027)
Controls	Yes	Yes
Adjusted R^2	0.590	0.416
Observations	2,719,686	3,584,722

Notes: In column (1), we analyze the extensive margin and we cluster the standard errors at the creator level. In column (2), we analyze the intensive margin, while we cluster the standard errors at the creator level and the token level. *p<0.1; **p<0.05; ***p<0.01

Table 4. Extensive and Intensive Margin Analysis

Existing vs. New Creators

From Figure 3a, we saw that there was a noticeable increase in the number of new creators that entered after the shock. In addition, from our analysis of the creation side, we found evidence suggesting that after the shock both the existing and the new creators created more tokens but exerted less effort in the tokens they created. Hence, it is important to understand whether the reduction in engagement is driven by the tokens created from one of the two groups of creators (i.e., existing or new ones). Once again, we study the two types of creators separately but we are unable to present the results due to space limitations.

First, we analyze the tokens of existing creators. Before the introduction of lazy minting creators could only introduce their tokens into the market by paying a fee, while afterward they could also do so for free. The zero entry costs could lead these creators to introduce work that is less engaging to Rarible's audience. We investigate this by applying the last specification of Table 3 on the subsample of tokens created by new creators. The coefficient estimate is similar in magnitude and significance to that of Table 3, suggesting that the lazy tokens tokens that existing creators introduced are less engaging to the audience of Rarible, even while controlling for the potential confounders. We dig deeper into this to understand whether all existing creators are affected the same. For this analysis, we use the pre-shock data associated with existing creators and for every existing creator we compute the average number of likes they received across all their tokens. Subsequently, we use this ratio to categorize existing creators into (engagement) quartiles that relate to their tokens' overall engagement with the Rarible community. We run our main specification separately for every quartile and we find evidence suggesting that those (existing) creators whose tokens were the most engaging before the shock (quartiles (3) and (4)), face higher engagement declines compared to the rest (quartiles (1) and (2)). We take this as evidence for the democratization of engagement. After reducing the costs of minting to creators, the engagement is distributed more equally across tokens, driven by a decrease in the engagement of tokens whose creators were most engaging before the introduction of lazy minting.

We also analyze the tokens of new creators, using our previous definition of new creators. We apply the last specification of Table 3 on the subsample of tokens created by new creators and we find marginal evidence ($p \sim 0.065$) suggesting that the tokens of creators who entered the platform shortly after the introduction of lazy minting, are less engaging, compared to the tokens of creators who joined shortly before.

Mechanism

Effort

A potential explanation behind the reduced engagement of Rarible members with lazy tokens could be that creators invest less effort in these tokens. Indeed, in our analyses of creation effort we found that creators exerted less effort in the tokens they created after the shock compared to those they created before the shock.

Attention

Another potential explanation behind the reduced engagement is that of token attention being distributed across more tokens. As we saw from Figures 2 and 3a, after the introduction of lazy minting, the number of new creators and new tokens increased many times over. If Rarible users' attention (e.g., token views) did not have the same rate of increase, then the attention would need to be distributed across a larger number of tokens compared to before the shock which would in turn be reflected in a lower engagement (i.e., average number of likes). Unfortunately, the API of Rarible does not allow us to extract the token views which would be an ideal measure of user attention. To deal with this, we use as a proxy for the attention of token i the total number of followers that the token's creator had up to the period that token i was introduced. For every period, we split creators into quartiles, depending on their total number of followers up to that period. Then, we use this split, to assign tokens into four respective groups. However, since, the median of the total number of followers is equal to the first quartile (zero) for every period, we combine the groups referring to the first and second quartiles into one. If the decline in engagement is driven by token attention being redistributed, we expect the strongest decrease for creators with fewer followers, as their larger follower count shields them. We rerun our main specification for each of the three groups and unlike what we expected, we find that those tokens whose creators have the larger follower counts (quartiles 3 and 4) are affected the most.

We extend this analysis by examining whether this decrease in engagement stems from reduced engagement from followers or non-followers. We consider engagement from a follower if the follower was following the creator of token i when the engagement (like) occurred. Our micro-level data allows for this analysis, as we have the timestamp of each like and follow occurrence. From the analysis of likes received from followers we find that the coefficient estimates of the tokens of creators assigned to the lower quartile (quartile 3) are insignificant at the 10% level, while those of creators assigned to the highest quartile (quartile 4) are negative and significant at the 1% level. This provides no evidence to support that a higher follower count can shield users from the engagement decline - consistent with the results of Table 5. In fact, the results indicate that the tokens of creators assigned to highest quartiles face a reduction in the engagement received from followers.

From the analysis of likes received from non-followers we find that the coefficient estimates are negative and significant at the 1% level across all quartiles, meaning that all creators receive less engagement from non-followers. This indicates that platform members' attention is distributed among more tokens after the introduction of lazy minting.

Lazy Minting Signal

We made a case for why lazy tokens are not easily identifiable by users. However, if our assertion is incorrect, then lazy minting could be a signal for low creation effort and thus lazy tokens could be less engaging (i.e., receive less likes). Hence, we also check whether lazy tokens provide a signal that leads to lower user engagement with these tokens. To do so, we focus our analysis on minted tokens introduced after the shock and use propensity score matching to create comparable samples of regular and lazy tokens. We assess the matched sample and find that it is relatively well-balanced. We apply our main specification on this match sample and we find that the coefficient estimate is insignificant at the 10% level, indicating that whether minted tokens were created using the lazy minting option is not a signal that affects members' engagement with those tokens. Hence, the evidence does not support the argument that lazy tokens provide a signal which subsequently drives our engagement results.

Platform Effects

With our analysis so far we have investigate how the introduction of lazy minting has affected the creation of tokens and the engagement of platform members with those tokens. We continue by conducting "back-of-the-envelope" calculations to analyze how Rarible's key performance indicators such as platform visits and transaction volume are affected. To investigate platform visits, we use website traffic data from Similarweb[20], while to investigate transaction volume, we use data from multiple other data sources such as DappRadar, NonFungible, and Rarible's API. For each metric, we compare the performance of Rarible with that of two competing platforms that serve as counterfactuals due to their similar trends before the shock. The comparison is conducted through multiple difference-in-differences analyses where we use different time windows for the period after the shock to test the robustness of our results. On average, we estimate that the introduction of lazy minting increases the number of platform visits by about 46.6 thousand which is an increase of about 60.3%, while the average transaction volume increases by about US$ 67.8 thousand which is an increase of about 196.17%. Considering that at the time Rarible's fees for every transaction were about 5% in total[21], this is an increase of about US$ 3.34 thousand in average daily revenue.

Conclusion

In this work, we examine how reducing content creation costs for creators impacts the key market outcomes. For our setting, we use an NFT market and the introduction of a new policy called "lazy minting". Through it, users were able to create tokens without incurring any fees. We analyze implications from two angles: (1) creation and (2) engagement. First, with regard to the creation aspect, we provide evidence for a volume-effort trade-off in that after the introduction of lazy minting, creators increase the volume of tokens that they introduce into the market but they exert less effort in crafting the tokens created via lazy minting option, which has become the prevailing mode of minting. Second, from the user engagement side, our results indicate that lazy tokens receive lower engagement (i.e., likes) in comparison to regular tokens. By analyzing the extensive and intensive margins, we find that this is not driven by lazy tokens receiving no engagement but by lazy tokens receiving less engagement. In addition, the evidence suggests that the creators who are more strongly affected are those whose tokens were on average more engaging up until the shock, implying that engagement is democratized after the shock. Third, analyzing the mechanism behind the results of the engagement side, we find that our results are driven, at least partially, by the reduced effort that creators exert when creating their tokens, as well as by reduced token attention. With the same analysis, we also find no evidence to support that a large follower count shields users against the engagement decline.

All in all, lazy minting can allow the platform to grow its available user-generated content and revenues

[20]https://www.similarweb.com/
[21]https://web.archive.org/web/20230218231437/https://rarible.com/blog/lower-fees/?fees_lower-fees-article

through commission fees[22]. Nevertheless, the studied implementation of lazy minting that allows unlimited entries with zero cost for creators, can lead to a reduction in user engagement which ultimately can hurt the platform. To limit the downside, while still keeping the upsides of lazy minting, the platform may take a governance measure of limiting but not abolishing lazy minting. One example of such an approach is the following: every user could be allowed to create an "x" (limited) amount of lazy tokens, once they create their accounts. This middle-ground solution would allow the platform to attract new work (either by current or new users) into their market. A potential concern is that users will have limited opportunities to create lazy tokens. To address this, platform owners can allow users to create a greater number (greater than "x") of lazy tokens. Nevertheless, to avoid flooding the market with new tokens, the platform owners may consider not making these tokens available for purchase (as "DALL·E 2" does with image creation[23]). An alternative route, would be to allow users to redeem one additional lazy token for every lazy token that they sell or burn. This would allow creators to keep using lazy minting without flooding the market with tokens, especially tokens that others do not find interesting.

Our work contributes to three streams of literature. First, our work extends the stream studying entry barriers in information goods markets by (1) studying the impact of a reduction in the marginal creation costs and (2) a case where the information goods have non-zero costs. Second, our study contributes to the existing body of research on platform scaling by examining the impact of a policy designed to expand the supply side of the platform on effort and engagement. Third, our work adds to the emerging literature on the creator economy and NFT marketplaces. In terms of practical applications, our results emphasize the importance for platforms to thoroughly evaluate the pros and cons of implementing supply-side scaling policies and they highlight the importance of developing tools that address the potential effort and engagement side-effects.

Our research is not without its limitations. First, we use data from only one marketplace which could affect the generalizability of our results. We refrained from using data from OpenSea because account creation on OpenSea was costly until June, 2022[24]. This means that market entry was not entirely free for creators - as in the case of Rarible - thus making this a less ideal setting for our study. Moreover, OpenSea has had platform vulnerabilities[25] making it a target for hackers[26]. This could have affected the platform's usage. Second, our observation window only spans about 6 months after the introduction of lazy minting. This however was a deliberate choice given that in the second quarter of 2022 Rarible underwent several updates, such as reducing its fees down to 1%[27] which could impact our studied metrics. Third, we do not have the digital files of the studied tokens. Having these files would have allowed us to enrich our analysis by incorporating further variables generated from them. Finally, we do not have direct measures of creator effort and token attention but we use proxies instead.

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[22]In Appendix 3., we conduct a series of "back-of-the-envelope" calculations on how the platform is affected in terms of platform visits, transaction volume, and new token volume.

[23]Users of this service are given 50 free credits that they can use to generate images. If the users needs more credits, they can purchase them directly from the platform.

[24]https://twitter.com/opensea/status/1536756398545158152?lang=en

[25]https://www.theverge.com/2021/10/13/22723092/opensea-nft-vulnerability-gift-security-researchers-wallet-hack

[26]https://www.theverge.com/2022/2/20/22943228/opensea-phishing-hack-smart-contract-bug-stolen-nft

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