Tokenomics Impact on User Behavior: Observations from NFT-Collateralized Lending Platforms

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Abstract

Featuring a platform-specific token has become the norm for cryptocurrency applications in recent years. This shift is driven by the growing emphasis investors put on "tokenomics" to assess the economic value of a cryptocurrency platform. Tokenomics refers to the economic model driven by the token associated with the platform. It includes the design of the token's utility, supply and demand, and distribution. Are tokenomics as important as claimed? Do they significantly influence user behavior? To help answer these questions, we measure NFT collateralized lending marketplaces, which – at their peak – provided a controlled field experiment. On the one hand, one platform, Blend (short for Blur Lending, the largest NFT lending platform by volume), features sophisticated tokenomics; on the other hand, two competing platforms, NFTfi and Arcade, rely on far simpler tokenomics. Our quantitative analysis reveals that even though users are trading essentially the same underlying assets, their behaviors, such as the loan terms they offer or consent to, are vastly different across these platforms. We further investigate user interactions within these platforms, and discover lender concentration on some of them (e.g., the top 10% of lenders on Blend are responsible for 32% of all money loaned). We also evaluate the impact of token design on user profitability, investigate token circulation and utility, and discover that users face significant risks, that they, along with regulatory bodies, should carefully assess.

I. Introduction

The emergence of the ERC-20 standard (for Ethereum) and its counterparts (e.g., SLC for Solana, BEP-20 for Binance Smart Chain), which allow the deployment of a cryptocurrency or application token on top of an existing, widely-adopted blockchain, has made it considerably easier for myriad new tokens to enter the market. However, while technical barriers to entry have been greatly lowered, if not removed, the question of economic incentives remains: when anybody can deploy a new token literally in minutes, how does one get investors interested in that token? Trying to answer that question has ushered in vibrant research activity around "*tokenomics*," which broadly refers to the set of incentives and strategies to foster token adoption, govern its distribution and regulate its supply and demand.

"*Airdrops*" are one of the earlier examples of tokenomics. In an airdrop, newly issued tokens (initially with no value) are gifted to selected users (e.g., social media influencers, large cryptocurrency portfolio holders, etc.). The idea is that these users now have an incentive to take action to make the token appreciate in value, which in turn drives the profitability of the issuing platform or project. Airdrops became particularly popular when several well-known applications, such as Uniswap [1], Ethereum Name Service (ENS) [2], and LooksRare [3], relied on them to launch their platform-specific tokens. In light of these successes, developers were drawn to spend more resources on tokenomics design, for instance, by creating mechanisms that use tokens as a form of voting shares to decide on a project's or platform's governance.

Tokenomics have also sparked research into multiple directions spanning from understanding the function of tokenomics in business operations to their impact on user participation. From the business perspective, studies include identifying the role of the tokens in the blockchain-based ecosystem [4], and how a well-designed tokenomics model can yield the same payoffs as equity and debt [5]. From the user participation standpoint, studies include evaluating different token distribution strategies for user adoption [6], analyzing the relationship between token compensation and user engagement [7], or demonstrating the (lack of) influence of airdrops on user retention and conversion [8].

However, past studies on the impact of tokenomics on users either 1) mainly focus on participation—user adoption, retention, conversion, or engagement—and do not investigate the impact of tokenomics on user behavior *within* the application (e.g., actual application usage, interactions with other users, use of the token, and overall profitability); or 2) do not consider the difference in quality and appeal of the underlying applications. That is, whether the impact on users are due to the tokenomics or the application itself is an open question.

Here, we propose to address this literature gap by studying user behavior on platforms with the same underlying application, but with different tokenomics. Specifically, we look into financial applications of non-fungible tokens (NFT). Initially garnering significant attention as a technology to provide incontrovertible public proofs of ownership for digital items [9], [10], NFT popularity reached an all-time high in 2021 when items in collections such as CryptoPunks and Bored Ape Yacht Club (BAYC)

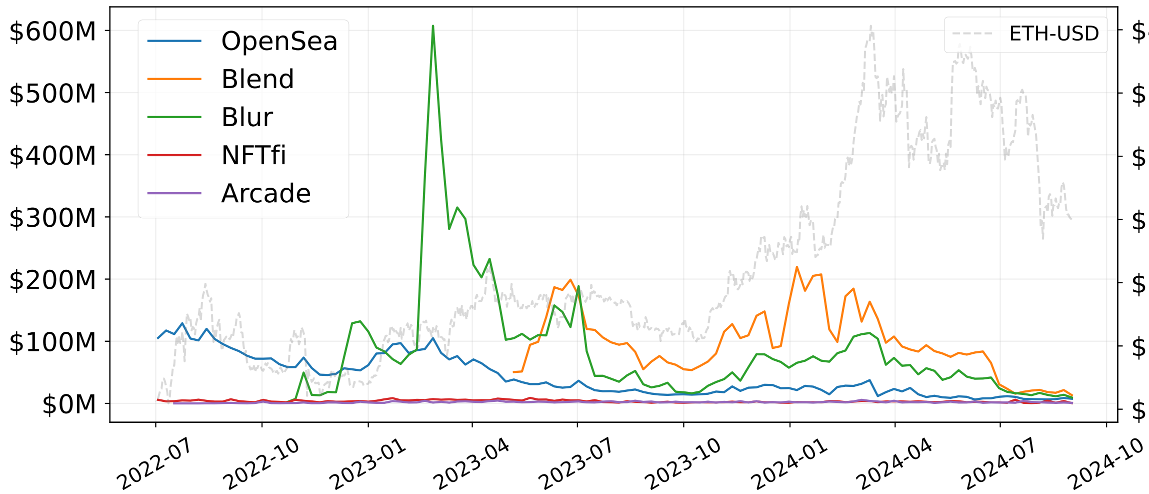


Fig. 1: **The weekly trading volume of OpenSea, Blur, and weekly lending volume of Blend, NFTfi, Arcade.** The y-axis on the left is the trading or lending volume in USD. The y-axis on the right is the ETH-USD price.

sold for hundreds of thousands of U.S. dollars. However, the hype quickly subsided. NFT trading volume was down 80% by early 2022,[1] and NFT holders struggled to offload their assets [11].

This downturn led the community to propose new applications for NFTs. In particular, a proposal that gained traction was to use NFTs as collaterals in peer-to-peer lending—similar in spirit to using art as collateral in traditional banking loans. At loan establishment time, the borrower mortgages an NFT with a value commensurate to the loan principal. If the borrower fails to repay the loan, ownership of the NFT is transferred to the lender. This assumes that over the (short) loan lifetime, the NFT will roughly hold its value.

By mid-2023, this novel use of NFT as collaterals had supplanted traditional NFT trading. To wit, Fig. 1 shows the weekly trading volume of various NFT-related platforms.[2] OpenSea, a "traditional" NFT trading marketplace, had the largest marketshare until late 2022. As the NFT bubble collapsed, OpenSea was quickly overtaken by Blur, the trading platform that heavily promoted their token-based incentives. In 2023, Blur spun out the Blend lending platform, which quickly became the market leader. Since mid-2024, the NFT market pretty much "went to zero," but we argue that there are still very valuable lessons we can learn from the whole episode.

Notably, because we can directly compare Blur (and Blend) with two other peer-to-peer NFT-backed lending platforms (NFTfi and Arcade) with different, and much simpler, underlying tokenomics, the NFT lending ecosystem provides a natural field experiment we can rely on *to assess the impact of tokenomics on user behavior*. In particular, the fact that NFTfi and Arcarde failed to get meaningful traction despite an earlier market entry, while Blur/Blend traded tens of millions of dollars (if not hundreds) at its peak will help us derive some insights about some of the major drivers for user adoption.

More precisely, loans on NFTfi and Arcade typically advertise high interest rates (e.g., 100–1,000% annually) to incentivize lenders to provide liquidity. On the other hand, loans on Blend commonly feature 0% interest rates. Intuitively, these terms should *repel* lenders who stand to lose money for each loan. To compensate, Blend features sophisticated tokenomics designed to provide participatory incentives, and these incentives have propelled Blend to the leading share of market for a considerable period of time.

In short, NFT lending platforms provide a unique opportunity to measure the impact of tokenomics on user behavior. We investigate user behavior through the prism of offered and accepted loan terms in Sec. V-A, lender-borrower relationships in Sec. V-B, user adoption and engagement in Sec. VI-A, and user profitability/compensation from rewards in Sec. VI-B. By collecting and measuring Ethereum blockchain data, we show that tokenomics significantly impact user behavior, to the point of overshadowing the underlying applications (here, NFT lending), in turn resulting in considerable financial risk for users.

II. Background

We start with some necessary background on concepts central to our discussion.

A. Cryptocurrency, Decentralized Finance, and Tokenomics

Cryptocurrencies are digital assets originally designed as a peer-to-peer payment method that avoids relying on a central authority [12]. Transactions are stored in a public, distributed ledger data structure ("blockchain"). Notwithstanding their

[1] https://www.theblock.co/data/nft-non-fungible-tokens/nft-overview/nft-trade-volume-by-chain

[2] OpenSea data acquired from DefiLlama https://defillama.com/protocol/opensea.

original purpose as payment systems, cryptocurrencies are now primarily used as speculative assets [13], and exchanges have started to offer even riskier cryptocurrency derivative products, despite low odds of long-term investor profits – particularly for retail investors [14].

At the same time, inefficiency remains a challenge for traditional financial and FinTech services due to centralized control, limited accessibility, and lack of interoperability. Decentralized Finance (DeFi) is an attempt to overcome such inefficiencies with blockchain technology [15], [16]. DeFi applications emphasize transparency, security, and decentralized governance. Service providers deploy smart contracts on blockchains to define their service offerings, and frequently make contract source code available for examination. Taking advantage of these desirable features, a number of DeFi services have been launched since 2017 [17].

The tokenomics model refer to the design of the utility, supply and demand, distribution, and circulation of a token. Many DeFi services adopt the decentralized autonomous organization (DAO) governance model and issue "governance tokens" to qualified platform participants [18]. Holders of governance tokens can directly vote on the direction the DeFi service should take. Anyone interested can receive governance tokens by keeping ("staking") money in a designated wallet, being gifted tokens by the issuer in exchange for meeting certain conditions ("airdrop"), or buying tokens on exchanges. Governance tokens are speculative assets, since the value of the token might appreciate if a project becomes successful and draws significant interest.

B. Non-Fungible Token Marketplaces

Blockchain technology ensures tamper-resistance and transparency in record-keeping; this opened the door to "non-fungible tokens," or NFTs, which initially were designed as incontrovertible public proofs of ownership for digital items (e.g., artwork, virtual real estate, etc.). NFTs considerably rose in popularity in the early 2020s, and fostered a vibrant ecosystem of marketplaces to trade them. As described in Section I, among these marketplaces, OpenSea initially rose to prominence – accounting for more than 90% of all trading volume – before being supplanted by the Blur marketplace, which relies on tokenomics. While Blur is not the only tokenomics-based NFT marketplace, competitors such as LooksRare and X2Y2 never seized significant market share; this has been attributed to Blur's unique reward program and generous compensation for customers that strictly trade on the platform [19].

When the NFT trading bubble burst in early 2022, NFT holders were eager to find new ways to unlock liquidity, and new forms of NFT-supported transactions started to appear: peer-to-peer lending, peer-to-protocol lending, and NFT rentals, to name a few. Peer-to-peer lending platforms (e.g., NFTfi, Arcade, Blend) use NFTs as collateral for the value of the loan; the platform itself does not keep direct custody of the NFT. In peer-to-protocol lending services, such as BendDAO and JPEG'D, borrowers directly lock their assets into the DeFi platform (protocol) and borrow from them. This often results in more stable loan terms but also less flexibility. NFT rentals often happen in gaming or metaverses as those NFTs may represent in-game items or virtual property, and renters pay a fee to use the NFTs for a period of time often to satisfy a certain requirements.

C. Collateralized loans

A collateralized loan is a contract between a lender and a borrower that uses a valuable asset as collateral as security. The borrower borrows *principal*, a sum of money, from the lender. This process is also referred to as loan origination. The borrower's cost of borrowing money is commonly represented as *Annual Percentage Rate (APR)*. APR is a measure of borrowing cost normalized for the length of the loan contract, helping to assess the cost of each loan on an equal basis:

$$APR = \frac{\text{Interest} + \text{Fees}}{\text{Principal} \times \text{Loan Duration (day)}} \times 365 \ .$$

At the end of each loan, the borrower either repays the debt (principal and interest) and retrieve the collateralized asset or *defaults*, that is, forfeiting the asset to the lender. The lender then *seizes* the asset and (potentially) resells it to offset their monetary loss. During an active loan, the borrower can choose to *refinance*, i.e., to switch to more appealing loan terms (duration, interest rate), often from other lenders.

D. High-risk traditional loans

Comparing to traditional, consumer finance, the NFT loans more closely resemble "payday loans" in terms of high-interest rates and short durations. High interest rates are generally viewed as harmful to borrower long-term financial status. In particular, institutions that primarily provide loans to underbanked or unbanked individuals are subject to stringent financial regulations. These institutions may have a valid reason to charge higher interest rates than traditional bank loans due to the relatively higher credit risk involved; yet, financial regulations in most jurisdictions control the interest rate to ensure that borrowers are not unduly burdened. For example, state legislation sets ceilings for the maximum interest rates in the U.S. [20]. Payday loans have been a focal point of studies for economic researchers. Some suggests it could have a positive effect due to improved access to financial services [21], [22], others argue that it has a net negative impact on borrowers because of accruing interest [23]–[25]. To monitor potential harms, the U.S. Consumer Financial Protection Bureau (CFPB) supervises consumer-finance businesses and regularly publishes reports [26]–[28].

III. Related work

We separate related work between relevant literature on tokenomics, and contemporary work on NFTs.

A. Tokenomics

There have been abundant research efforts in tokenomics, ranging from understanding the functions to designing tokenomics models. Studies focusing on understanding the functions of tokenomics include identifying the role of the tokenomics in the blockchain ecosystem [4]; how tokenomics models can function similarly to equity and debt [5]; investigating the relationship between token functions and token price [29]. Research on the design of tokenomics include evaluating how tokenomics models decrease the entry cost and accelerate adoption [30]; justification for developers to choose such a costly token distribution method [31]; and explaining how airdrops can help expand the user base and driving up the value of an exchange [32].

In the middle of the spectrum, and closest to our work in this paper, we find research on the study of the impact of tokenomics on users, such as evaluating the effectiveness of airdrops on user adoption and retention [6], [7]. Our work expands that research area by investigating the impact of tokenomics on user behavior *within* a platform, in addition to users entering and exiting the platform.

B. NFT

The NFT hype brought research interests from diverse communities, such as security and privacy [33]–[36], social behavior [10], [37]–[39], network analysis [40], [41], and finance [42]–[44].

Different from these efforts, our work produces a quantitative measurement study of user behavior, and uses it to derive possible effects of tokenomics. In particular, we observe that users are willing to gamble on long-term valuation of governance tokens, even when the underlying market (here NFT trading) is cratering; of course, the effect is only transient.

IV. Data

In this section, we describe how the data is collected and the fundamental mechanisms of the lending platforms.

A. Collection

Similar to all cryptocurrency applications, all trading and lending records of these three platforms are stored on the Ethereum blockchain for transparency. Trading data includes buyer, seller, price, timestamp, and the NFT traded. Lending data includes all loan details: lender, borrower, loan principal, duration, interest rate, event (loan origination, refinance, repayment, and default) timestamps, and the underlying NFT collateral.

We first obtain a list of smart contract addresses related to each platform from their official documentation, and scan for the event logs emitted by these addresses from a self-hosted Ethereum node. We acquire the smart contracts' Application Binary Interfaces (ABI) from Etherscan[3], an indexed Ethereum blockchain explorer, to decode the logs and extract trade and loan details. Our collection interval ranges from the launch of (each of) the platforms to August 31, 2024, 11:59:59 PM UTC (block 20651993).

B. Lending platforms

Blend, short for Blur Lending, was introduced on May 1st, 2023. Blend has two unique features: 1) Perpetual loans, 2) Dutch auction exit. All loans on Blend are originated with a principal and a fixed interest rate but without an expiration date. Borrowers can repay loans at any time to withdraw their NFT collateral, in which case the debt is calculated at the time of repayment. Borrowers can also refinance, i.e., exit the loan position and find a new loan term. The idea is to provide borrowers the freedom to negotiate a more desirable loan with others. If a lender wants to exit the loan position, they can trigger a 30-hour Dutch auction that starts with an interest rate set to zero, which automatically increases until a new lender is willing to take over. If the interest rate reaches a predetermined value without lenders taking over and the borrower has not repaid the loan by the end of the auction, the borrower defaults, and the collateral is transferred to the lender.

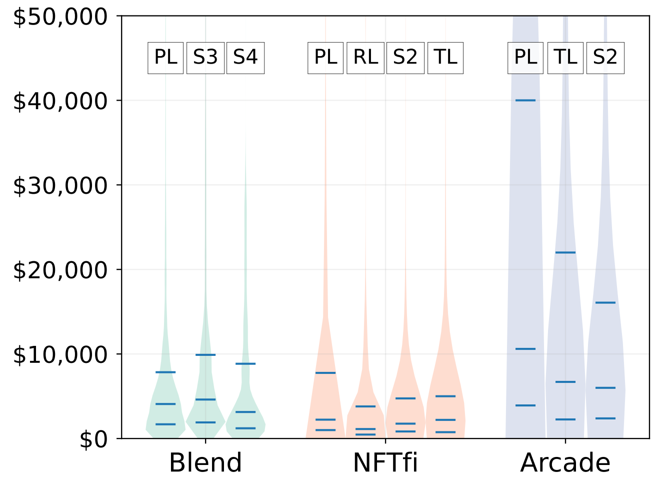
NFTfi was launched on May 14, 2020. It is the oldest peer-to-peer NFT lending platform and was the largest by lending volume before Blend. NFTfi offers a straightforward lending mechanism: A borrower and a lender agree on principal, interest, and duration.

Arcade is the second oldest NFT lending platform, and launched on Aug 30, 2021. Arcade's lending mechanism is intuitive, similar to NFTfi. The main appeal of Arcade is that it allows borrowers to bundle multiple NFTs together to increase the loan value [45].

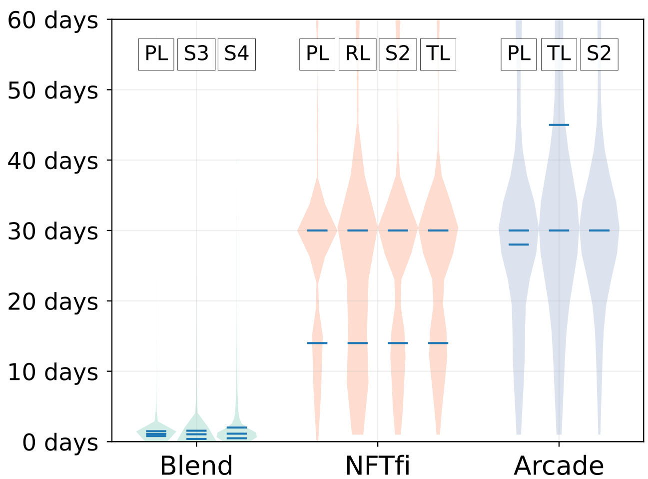
On Blend and Arcade, users are not subjected to any protocol fees. The tokens offered to users not only serve as a reward, it's also the main business model as the platforms still hold the vast majority of the supply. On the other hand, NFTfi, which does not issue a token, charges a 5% protocol fee to lenders.

Date	**Blend**	**NFTfi**	**Arcade**
2020-05-14	–	Platform Launch	–
2021-08-30	–	⋮	Platform Launch
2023-05-01	Platform Launch	⋮	⋮
2023-05-15	⋮	Reward Point Launch	⋮
2023-10-25	⋮	⋮	Token Launch
2023-11-20	Season 3 Start	⋮	⋮
2023-11-28	⋮	Season 2 Start	⋮
2024-04-01	⋮	⋮	Season 2 Start
2024-04-08	⋮	Token Launch	⋮
2024-06-26	Season 4 Start	⋮	⋮

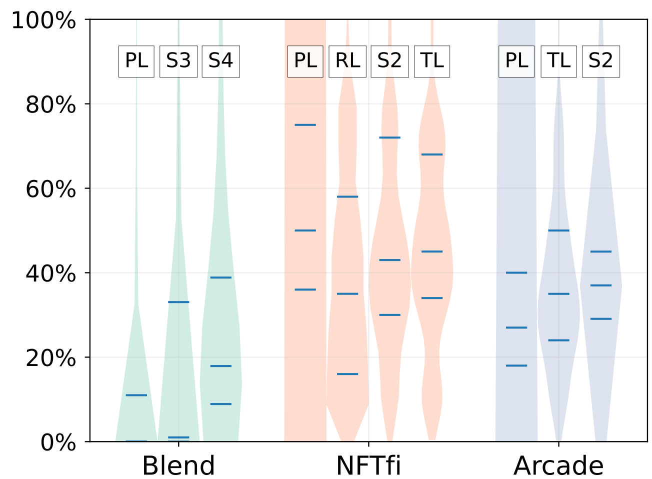
(a) Major event timeline.



(b) Principal



(c) Duration



(d) APR

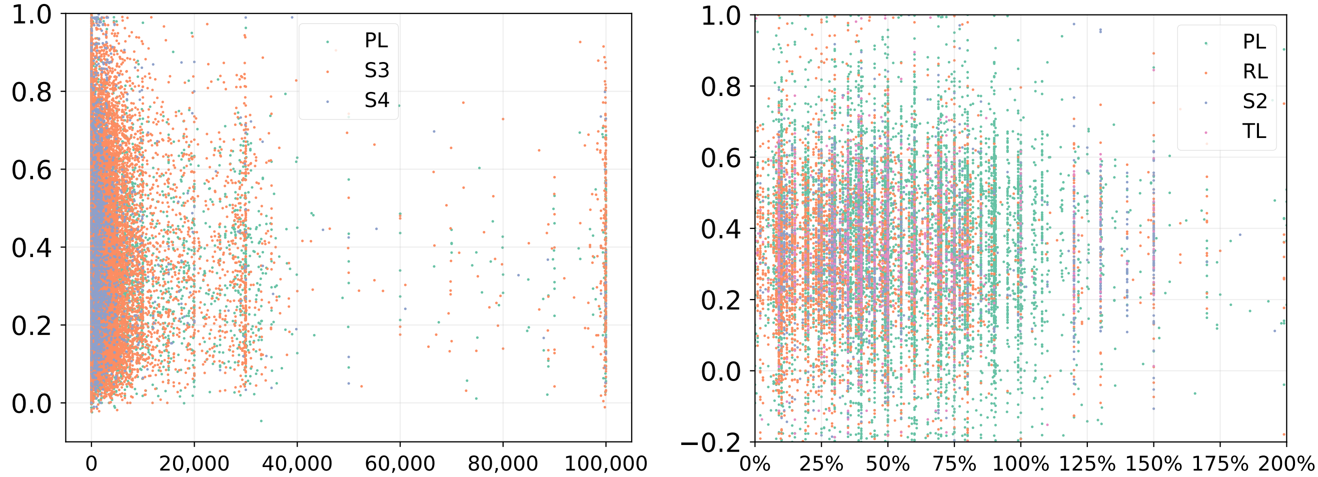
Fig. 2: **Loan term distribution between the events for each platform.** Fig. 2a shows the major event timeline for each platform, '–' denotes that the platform did not exist yet. For Fig. 2b, 2c, 2d, the text on top of each violin plot is the abbreviated event name (PL is short for Platform Launch in Fig. 2a), and the corresponding violin plot is the distribution starting from that event to the next event. For example, in Fig. 2b, Blend's first violin plot is the distribution of the loan principals from PL (Platform Launch) to S3 (Season 3), and the rightmost violin plot is from S3 to the end of our measurement. Blue horizontal lines in each violin plot indicate the 25th, 50th, and 75th percentile.

C. Platform major events and incentive structure

Platforms evolve and introduce new content over time. We identify and focus on the introductions most relevant to tokenomics and denote them "major events." Fig. 2a shows the timeline of the major events on each platform. Blend, from its launch, offered their parent platform governance token, $BLUR, as rewards to incentivize users to provide liquidity. NFTfi was operating without rewards for three years and introduced a point-based reward program shortly after Blend appeared on the market. However, the utility and value of these points raised major concerns since they were not redeemable, and served primarily vanity purposes. It was after nearly a year that NFTfi introduced its governance token, $NFTFI, for point holders to redeem. On the other hand, Arcade launched a reward program and introduced their governance token, $ARCD, at the same time.

Major events also include *Season* starts (which also mark the end of the previous season). Similar to online video games [46], each platform rolls out "seasonal" content to encourage user engagement. During a given season, participants engage with the platform and compete with each other to earn rewards. At the end of each season, participant performance is calculated and rewards are distributed. Only at this time can participants realistically evaluate whether the rewards meet their expectations

[3]https://etherscan.io/



(a) Blend

(b) NFTfi

Fig. 3: **Haircut (y-axis) vs. interest rate (x-axis) in basis points (Blend) or APR (NFTfi).**

and whether to adjust their behaviors accordingly. Platforms also tend to align the introduction of new content with the start of their seasons. For example, the launch of Blend coincided with the beginning of Blur's second season; NFTfi's Reward Point launch occurred around the same time as the start of its first season, while its Token Launch aligned with the beginning of season three. Similarly, Arcade's Token Launch marked the start of its first season.

Participants' in-season decision-making largely follows a reward-earning guideline provided by the platform, which can change from season to season. Blend's reward-earning guideline stays consistent throughout season 2 and 3, which rewards lenders when they lend out 1) more loans, 2) larger principal loans, and 3) lower-interest rate loans (including 0% loans). Similar to Blend, NFTfi's reward-earning guideline stays largely the same throughout all the seasons, which rewards lenders to lend out 1) longer duration loans, 2) larger principal loans, and 3) loans with 2–10% APR. On the other hand, Arcade's reward-earning guidelines change from season to season. In Season 1, Arcade encouraged users to refinance/rollover loans, but then pushed users to lend in USD Coin (USDC) in Season 2.

V. Lending behaviors

We analyze lending behaviors before and after the major events introduced in Section IV-C. Specifically, we aggregate, for each platform, statistics between these major events up until the end of our collection to highlight behavioral differences.

A. *Loan terms on different platforms*

We show the loan terms (principals, duration, APR) distributions between the major events for each platform in Fig. 2. We can immediately see that loans *across* Blend, NFTfi, and Arcade have very different characteristics. First, loans on Arcade have in general the highest principal among the three (Fig. 2b). This could be attributed to the design of Arcade—borrowers can bundle multiple NFTs together into a single loan. Second, loans on Blend are typically finalized (either repaid, refinanced, or defaulted) in a very short period of time (1–2 days) compared to NFTfi and Arcade (Fig. 2c). This could be the result of the perpetual loan design and the tokenomics incentives, where lenders can exit the position whenever they want, i.e., as soon as they have met the criteria for collecting rewards for this loan. Third, loans on Blend have mostly zero-APR from platform launch to the start of Season 3, while APRs in NFTfi and Arcade are typically much higher.

Loan terms *within* each platform also exhibit distinct patterns over seasons. First, for NFTfi and Arcade, barring the high principals in the first observation period (PL) when NFTs were valued much higher on the markets in general, the loan principals see a increase from Reward Launch (RL) to Token Launch (TL) in NFTfi, and a decrease from Token Launch (TL) to Season 2 in Arcade. These trends align with the reward programs–NFTfi encourages lenders to lend out larger principal loans, while Arcade did not consider principals so that lenders can start more loans with lower principals to accumulate rewards. Second, Blend lenders starting to impose interests from Season 3 onward suggests that the token rewards are not as appealing as they used to be, and lenders were reverting back to interest to compensate their risks. Third, loans' APR on NFTfi started fluctuating after the reward program was introduced but always stayed lower than before Reward Launch. It is likely to reflect lenders' uncertainty of the reward. Loans on Arcade, on the other hand, presents a less instability in APR, which could be the result of the implementation of tokens rather than vanity points.

	Blend			NFTfi			Arcade		
	All	Lenders	Borrowers	All	Lenders	Borrowers	All	Lenders	Borrowers
Num. of Nodes	8,554	3,431	6,280	5,819	2,052	4,369	1,101	399	767
Num. of Edges	374,387	–	–	66,674	–	–	7,476	–	–
Density	0.0051	–	–	0.0020	–	–	0.0062	–	–
Transitivity	0.076	–	–	0.010	–	–	0.0079	–	–
Avg. degree									
- In-degree	43.77 (2.8)	51.00 (6.4)	59.62 (3.8)	11.46 (1.1)	5.45 (2.0)	15.26 (1.5)	6.79 (0.9)	2.65 (1.8)	9.75 (1.3)
- Out-degree	43.77 (4.0)	109.12 (9.8)	35.29 (5.2)	11.46 (1.1)	32.49 (3.2)	6.58 (1.2)	6.79 (1.4)	18.74 (3.7)	4.02 (1.7)
Avg. degree centrality [10^{-3}]									
- In-degree	5.12 (0.3)	5.96 (0.7)	6.97 (0.4)	1.97 (0.2)	0.94 (0.3)	2.62 (0.3)	6.17 (0.8)	2.41 (1.7)	8.86 (1.2)
- Out-degree	5.12 (0.5)	12.76 (1.1)	4.13 (0.6)	1.97 (0.2)	5.58 (0.5)	1.13 (0.2)	6.17 (1.3)	17.03 (3.4)	3.65 (1.5)
Total principal [10^9USD]	2.88			0.60			0.23		
LSCC									
Num. of Nodes		919			36			3	
Num. of Edges		95,665			202			8	
Density		0.1134			0.1603			1.33	
Transitivity		0.2685			0.0916			0	
Total principal [10^9USD]		0.93 (32.6% of total)			0.001 (0.3% of total)			-	

TABLE I: **Statistics for the graph constructed from loan transactions.** The numbers in parentheses represent standard errors. (LSCC: Largest Strongly Connected Component.)

Next, we study loan *haircuts* across platforms. Typically, the size of the haircut strongly correlates to the risk of the underlying asset where riskier assets receive larger haircuts. It is the percentage difference between an asset's market value and the amount used as collateral for a loan:

$$h = 1 - \frac{\text{principal}}{\text{collateral value}} .$$

We use the median of the most recent historical sales price of the NFT collection for the collateral value. The closer h is to zero, the closer the loan principal is to the market value of the collateral. The value of the collateral is frequently, but not always, greater than the loan principal (i.e., h can be negative).

Fig. 3 plots, for each loan, the haircut vs. the interest rate on Blend and NFTfi. The interest rate is in basis point for Blend and in APR for NFTfi, since APR is not available in Blend's perpetual loan design. Holding expectation of collateral value fixed (as is the case with a specific NFT), offering a higher principal results in a lower haircut. However, a higher principal is riskier for lenders. So, to protect themselves against these higher costs, lenders typically charge higher interest rates. However, this negative relationship between interest rate and haircuts is not immediately observable on Blend across all seasons, and it is only slightly noticeable on NFTfi's first observation period (Platform Launch). The lack of negative relationships between interest rate and haircuts implies that lenders may be seeking to mitigate lending risks through other means, such as platform rewards.

B. *Lender-Borrower interactions*

We next aim to better understand how lenders and borrowers interact with each other. Edges are directed from lenders to borrowers. For ease of exposition, we will consider the users before the start of Season 3 for Blend, while considering all the users of NFTfi and Arcade.

To do so, we construct a directed graph $G = (V, E)$ from the lending transactions: nodes (V) represent parties to the loans and edges (E) loan contracts in G. We first consider the *graph density* (number of edges over the maximum number of possible edges). A higher graph density implies that cryptocurrency liquidity moves across many parties, while a lower density is consistent with borrowers receiving liquidity from a small fraction of lenders. We also consider *transitivity*, i.e., the global clustering coefficient, by constructing a undirected graph where lenders simply have a connection with the borrowers. Transitivity represents the fraction of all possible "triangles" (three nodes where each node is connected to the other two) in the graph that are actually present, and is a measure of how often nodes that are neighbors of the same node are neighbors of each other. The in- and out-degrees of nodes in G represent the number of borrowing and lending activities, respectively; we also explore in- and out-degree *centrality* (degree divided by the number of nodes minus one).

To further explore how tightly related the traders are with each other, we consider the *strongly connected components* in G [47], [48], the sub-components in which all nodes are accessible from any other nodes. These strongly connected components represent a group of people circulating assets and capitals among themselves. In conventional lending markets such as consumer financing, money flows from wealthy lenders to many borrowers, and almost never in the opposite direction, which means that few nodes are in strongly connected components. On the other hand, commercial real estate frequently relies on inter-bank loans, which could lead to such strongly connected components.

Table I summarizes the statistics about the graph G. The low density and trasitivity suggests that the neighbors of neighbors are not likely to lend or borrow with each other. It also shows that lenders in the platforms have non-zero average in-degrees, suggesting that they also borrow liquidity in the markets, though less frequently than lending. This suggests that the money flow in Blend is not one-directional from lenders to borrowers, but that lenders also participate in borrowing. Blend lenders have a particularly high in-degree, indicating they lend to multiple parties. The largest strongly connected component (LSCC) consists of only 10% of all nodes, but contributes 32% of all loan principals.

The above statistics imply that the lending community are highly concentrated—a few parties subsidize most loans in Blend. To examine this concentration, we run the Louvain community detection algorithm [49] on the Blend graph where the weights are the loan principals and resolution set to 1. The algorithm yields five large communities (>1,000 nodes). The result of the communities exhibit a star-like graph where a few nodes in the center are connecting to a significant number of nodes on the outside. In other words, major lenders borrow from each other, and lend to a large number of individuals, and this structure of connection persists with varying resolutions. Fig. 4 shows one of the communities.

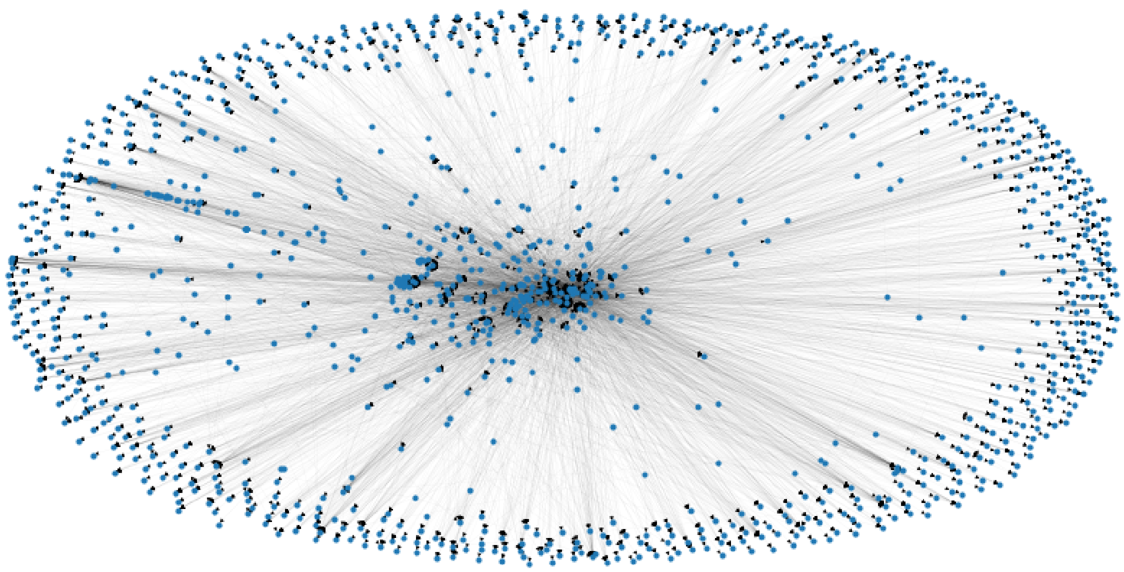


Fig. 4: **A community extracted from the Blend lending graph.** Arrows indicate the direction from lenders to borrowers. For visualization purposes, multiple edges between the same lender and borrower are aggregated.

VI. Reward system impact

The discussion so far has described the impact of different platform-dependent incentive systems on the terms of the NFT-collateralized loans. We now turn to the effect of these reward system on user adoptions; and how these rewards are used.

A. *User adoption and engagement*

Our first analysis shows the difference in the number of users before and after each major event. Fig. 5 depicts the weekly number of lenders and borrowers. We observe that Arcade's scale is negligible compared to NFTfi and Blend—to the point that we will not discuss Arcade any further in this section.

1) Blend: The number of lenders dropped significantly immediately after rewards were distributed at the end of Season 2. This implies that lenders were not satisfied with their reward, and decided to leave the platform. On the other hand, a large number of borrowers were present until the end of Season 3. Because Blend's reward system only incentivizes lending and does not reward borrowing, the negative perception of the reward from lenders did not affect the borrowers. However, without new features and the continuing lack of liquidity, the majority of the traders left the platform after Season 3.

2) NFTfi: The number of lenders immediately increased after NFTfi introduced the reward mechanism. However, this increase lasted only for a short period of time before the number dropped back to levels comparable to those seen before before. This appears similar to what we earlier observed in Fig. 2d with APRs which *increased* even after the reward system was introduced. In short, this behavior is consistent with users finding the reward points worthless and deciding to leave the platform.

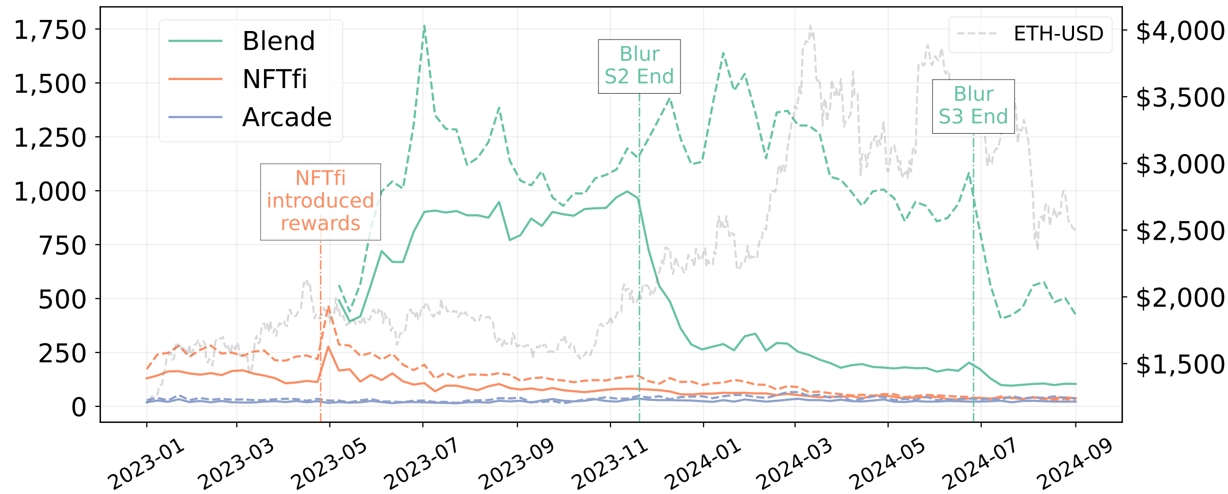


Fig. 5: **The weekly number of lenders (solid lines), borrowers (dashed lines) on Blend, NFTfi, and Arcade.** The y-axis on the left is the number of users. The y-axis on the right is the ETH-USD price.

B. Token reward profitability: Blend and Blur

We next attempt to more formally verify the above intuition that user adoption and engagement correlates to the major events. In particular, we set out to fully understand what happens right after Blur season 2, when many lenders drop out.

To understand how profitable the reward is, we analyze the full lending, buying, and selling histories[4] of all users in the entire Blur ecosystem. We construct the following notations: For each user that lends out a total of n_{le} loans, the principal lent is pl_i for each loan i, the corresponding repayment the lender receives is rl_i, and the value[5] collected from the defaulted NFT is sl_i. Partial repayments do not happen.[6] That is, if the borrower defaults, $rl_i = 0$; on the other hand, if the loan is repaid, $sl_i = 0$.

Likewise, we define n_{bo} as the number of loans the user borrows, pb_j as the principal borrowed for each loan j, rb_j as the repayment for loan j, and sb_j as the value of the defaulted NFT for loan j. Again, if the borrower defaults, $rb_j = 0$; if the loan is repaid, $sb_j = 0$. Therefore, the lending/borrowing Profit and Loss (PnL), PnL_{lending}, is:

$$\begin{aligned} PnL_{\text{lending}} = &- \sum_{i=1}^{n_{\text{le}}} pl_i + \sum_{i=1}^{n_{\text{le}}} rl_i + \sum_{i=1}^{n_{\text{le}}} sl_i + \\ &\sum_{j=1}^{n_{\text{bo}}} pb_j - \sum_{j=1}^{n_{\text{bo}}} rb_j - \sum_{j=1}^{n_{\text{bo}}} sb_j \end{aligned}$$

The user can also buy and sell NFTs. We use n_{buy} to denote the number of NFTs bought, $price_k$ to denote the price of each bought NFT k, n_{sale} to denote the number of NFTs sold, and $price_l$ to denote the price of each sold NFT l. Since rewards are paid in $BLUR tokens and the average token price within a week after season 2 ends is 1 $BLUR $\approx$ USD 0.50. We use this value to compute the reward R each user receives in USD. Therefore, the buying/selling PnL, PnL_{buysale}, and the final PnL, PnL, are then:

$$\begin{aligned} PnL_{\text{buysale}} = &- \sum_{k=1}^{n_{\text{buy}}} price_k + \sum_{l=1}^{n_{\text{sale}}} price_l \\ PnL = &PnL_{\text{lending}} + PnL_{\text{buysale}} + R \end{aligned}$$

Fig. 6 shows the statistics of top 100 users in terms of R received (i.e., the left most user, ranked 1, received the most reward). The top plot shows the reward amount (R), lending PnL (PnL_{lending}), buy-sale PnL (PnL_{buysale}), and total PnL (PnL) of the top 100 users. The bottom plot shows the number of loans lent (n_{le}), borrowed (n_{bo}), number of NFTs bought (n_{buy}), and sold (n_{sale}).

[4] Blur does not directly reward buying or selling, instead they reward "bidding" on on-sale items (don't have to be accepted) and "listing" items for sale (don't have to be bought), which would still indirectly affect the buying and selling activities. [50]

[5] Based on the calculation in V-A for the haircut study.

[6] For lenders, loans are always repaid in full even in a refinancing event, since the new lender pays off however much the borrower couldn't repay.

Fig. 6: **Top 100 users (ordered by rewards) statistics in Season 2.** The x-axis is the rank of the users in terms of token rewards for both plots. The y-axis is the PnL in USD for the top plot, and shows the number of trading actions for the bottom plot.

In the top plot, the total PnL line in pink shows that, despite a few traders making profit (user ranked 78, 91, 93), most of the users suffer from monetary loss—in some cases, millions of dollars. This is true even for many of the high-ranked users who were actively engaged with the platform. Moreover, PnL_{buysale} makes up a significant portion of the final outcome PnL, renders the reward inconsequential.

Focusing on the lending activities, the top plot shows that most of the users hold a neutral PnL from the lending activity itself (the orange line), despite the bottom plot indicates that these users lends out (and sometimes borrows) a significant number of loans. This is another clear indication that users are not using Blend's lending service to profit—it's a mean to accumulate rewards. These phenomena largely explain why a significant number of lenders dropped out of the platform after Season 2.

C. Token reward usage: Blend

Even though Blend and Blur users who received token rewards could cash out, they also have the option to *stake* these tokens in the platform to earn interest. In February 2024, Blur introduced an Ethereum Layer-2 solution, Blast, and users can deposit funds (ETH, or major stablecoins such as DAI, USDC) to enable staking. We trace the token transfers to understand whether users decide to stake.

Fig. 7 shows the $BLUR token staking and withdrawal timeline after Season 2, and the USD-pegged deposits to Blast. Users received in aggregate around 300M tokens after Season 2. They staked slightly more 600M tokens at the same time, and took them out just before Blast's launch. They then completely transferred out after Season 3, as all the activities and rewards are now happening on Blast. This is consistent with the Blur community encouraging users receiving $BLUR token rewards to first stake them, and then transfer them to Blast (after having converted them to ETH or a stablecoin) for maximal yield.

VII. Discussion

We next discuss the implications of our analyses, mainly the influence of tokenomics on user behavior, the risks to lenders and borrowers, and the fundamental challenges of incentive design.

A. First-mover advantages

NFTfi and Arcade attempted to retrofit a tokenomics model into their products, months or even years after the initial launch. While we observed *some* impact on users, that impact remain relatively small. Conversely, Blur was launched with a innovative design for how people could trade NFTs, and more importantly, included a tokenomics model from the start, and featured very generous airdrop campaigns. These features quickly attracted a significant amount of traders even during as the NFT price bubble was bursting.

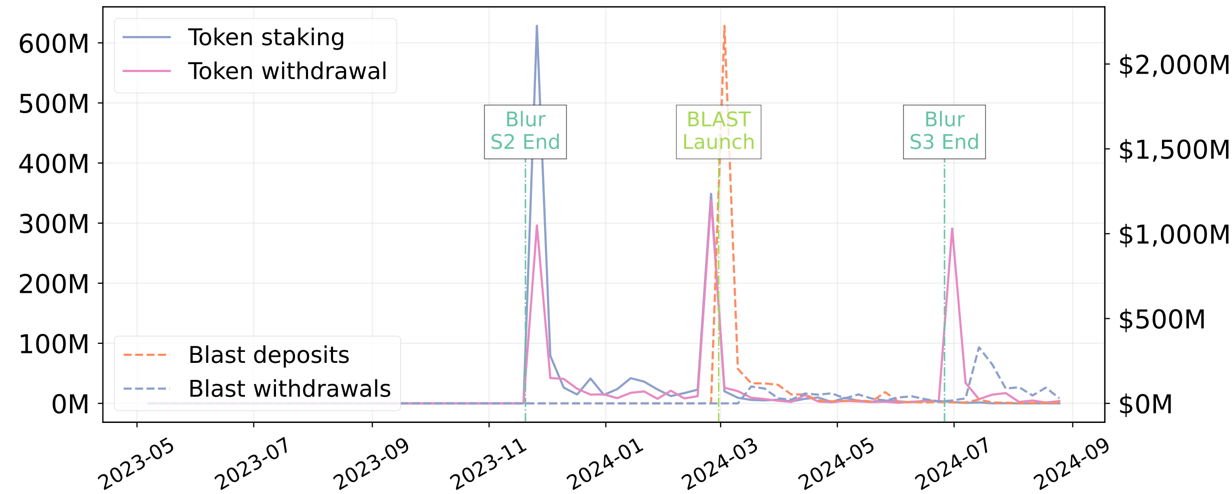


Fig. 7: **Token ($BLUR) movement and USD deposits to Blast.** The y-axis on the left is the number of the token for token deposits and withdrawals, while the y-axis on the right is USD for Blast deposits and withdrawals.

NFT lenders seemed very receptive to the token design: despite very unappealing loan conditions for them (e.g., zero percent interest rates), they considerably engaged with the platform. The hope was that token rewards were going to largely compensate them. As we saw however, this was not the case—many lenders faced significant losses in the end.

B. User retention challenges

Despite the successful token airdrop campaigns for user adoption, Blur, as well as most cryptocurrency projects, still need to achieve user retention for long-term profitability. Seasonal content has been widely used in video game industry, and the idea is now being applied in the cryptocurrency world. However, user engagement with cryptocurrency platforms is mainly driven by the opportunity to profit, thus the diversity of the seasonal content for these platforms is quite minimal. Blur is a striking example that as soon as the reward system become underwhelming (i.e., people lose faith in tokens eventually appreciating), users do not hesitate to leave. We also observed minimal user migrations to other platforms, and the decrease in engagement is a direct result that the entire NFT lending volume went down significantly.

C. Risks to participants

Following platform guidelines in hopes of recovering current financial losses with future rewards is a risky strategy, since the reliability of this source of income is largely unknown, especially as the prices of cryptocurrencies, including governance tokens, are highly volatile. The existence of significant co-movement between cryptocurrency volatilities is documented in several pieces of literature [51], [52]. Furthermore, Blend lender rewards (i.e., how many tokens a lender receives) are calculated based on their relative ranking compared to other participants of the entire Blur community. As shown in Section VI-B, most of the participants ultimately fail to recover their losses.

With its near-zero interest rate and perpetual loans, Blend sounds like a borrower's paradise: borrowers have, in theory, the ability to get money for (almost) free, forever. However, most lenders trigger the Dutch auction refinancing mechanism described in Section IV-B as soon as possible (i.e., within days of loan initialization), meaning that borrowers end up repaying the loan almost immediately, in case the refinancing interest grows out of hand and the loan liquidates, which in terms significantly lower the the potential usage of the borrowed capitals.

On the other hand, despite the platforms' avowed stance on prohibiting laundering behavior to earn tokens, it is unclear how this prohibition is implemented, and how severe this behavior impacts our results. We leave this to future study.

D. NFT finance

Blur and Blend were developed to generate liquidity for the dying NFT trading scene. Before their existence, NFT lending was filled with high-interest rate loans. High-interest rate loans indicate lenders low confidence in NFTs represented as collateral assets. The artificial liquidity and low-interest rate generated by Blur and Blend's tokenomics design rely heavily on users sense of novelty. Sophisticated financial playground featuring tokenomics may impact user financial behavior, but as long as the fundamental utility and value of NFTs stays largely the same, this influence will only be temporary—as evidenced by the fact that Blur and Blend are seemingly fading out as well in 2024.

2021–22 showed all the hallmarks of an economic bubble, with NFT collections (Boring Ape Yacht Club, CryptoPunks, and others) skyrocketing in valuation. However, by 2022-23, the bubble had largely burst, and many investors were far more bearish. While a resurgence to the levels seen in 2021 is unlikely, some have argued that the burst of the speculative bubble behind NFTs did not meaningfully alter fundamentally strong demand for NFTs.[7] To be sure, the idea of a traceable digital proof of ownership of a piece of art might still be appealing to many, and other NFT applications like property titles (e.g., for virtual real estate) might also have some economic value. Time will tell whether NFTs can fundamentally hold some value; our argument is that they have to, if they are to be used as collateral. The somber data from mid-2024 are consistent with that argument: NFT trading volumes (and values) have continued falling, and this time, they have been dragging NFT-collateralized lending platforms with them. However, the insights we observed from being able to directly compare different platforms with different tokenomics—notably the willingness of users to gamble on long-term valuation of governance tokens—are likely to apply beyond the context of NFT finance.

VIII. Conclusion

We studied the impact of tokenomics on user behavior—specifically application use, user interactions, user engagement, profitability, and token use—through three major peer-to-peer NFT lending platforms (Blend, NFTfi, and Arcade) using data collected from the Ethereum blockchain. We observed a number of idiosyncrasies: 1) Tokenomics drives atypical application use, such as zero-interest and extremely short-term loans on Blend; 2) Native tokenomics design on Blur and Blend have higher impact than "retrofitted" tokenomics (NFTfi, Arcade); 3) Attempting to recoup losses from low interest rate with the promise of future rewards results in extremely high risks to lenders; 4) User retention relies largely on the long-term profitability of the reward.

We identified distinct patterns in user behavior (e.g., completely different loan duration and APRs across platforms), and show that tokenomics design can shape financial activities in ways not observed on platforms with more conventional incentive structures. Additionally, our study highlights the importance of the potential downsides of token-based incentives.

Our analysis also evidences novel risks in peer-to-peer lending markets. While NFTs' heyday is—barring an unlikely resurgence—probably behind them, we argue that the characteristics of the NFT market—high uncertainty, rapid swings in market trends, extremely high-risk investments—are likely to periodically reappear as novel products are offered.[8]

We stress the importance of the balance between tokenomics and the value of the underlying application. Otherwise, we fear we might see the same story we described in the context of NFTs being played over and again: creative tokenomics design might entice users to participate in a platform for a while, even as the economic proposition is overall questionable, only to leave the platform, frequently losing money in the process, when it becomes clear that the underlying fundamentals are unsound and the relevant tokens fail to appreciate or even hold long-term value.

But, concretely, what are possible ways to provide at least some form of user protection? From a regulatory perspective, while transactions are mostly transparent (due to them being recorded on a blockchain), we see very little in terms of risk disclosure or user education on most platforms dealing in cryptocurrency-related products (including the NFT lending platforms we studied). We believe that this is an absolute must, so that potential investors can make better informed choices, rather than being influenced by hype cycles, and (except for a few lottery winners) seeing their investments vaporize.

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[7]See https://www.grandviewresearch.com/press-release/global-non-fungible-token-market for an example of optimistic long-term growth forecasts, partially motivated by the continued influx of venture capital.

[8]In early 2025, *meme* coins are an example of an "investment" with similar characteristics.

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