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Short Paper

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Abstract

Decentralized autonomous organizations (DAO) received many discussions and attempts recently with the rapid development of blockchain. Token incentive is one of its most important features and owns multiple attributes of equity, property, and currency. To explore its unknown effect, we utilize a quasi-experiment setting in the NFT marketplaces. We find that the token incentives with DAO implementation in Rarible can significantly motivate users' participation compared with SuperRare at the platform level. At the seller level, by the comparison of cross-platform users and only-OpenSea users, we find it significantly changes users' trading behavior which reflects in the increment in transactions number and average prices. However, through the equilibrium analysis based on the supply and demand model, the growth rate of the average prices is far beyond the magnitude it should be at the equilibrium state. Therefore, we argue that buyers' purchase decision is driven by the high expectations of token value.

Keywords: Decentralized autonomous organizations, token incentives, non-fungible token, false prosperity

Introduction

In the past decade, the rapid development of blockchain triggered the emerging attempt at decentralized governance (Chen et al. 2021). This new type of community, which is known as the decentralized autonomous organization (hereafter, DAO), means organizations are operated by crowd decision-making based on self-executing smart contracts rather than centralized governance (Hassan and De Filippi 2021). Its characteristics can also be summarized as distributed and decentralized (based on the distributed network, no central authority, and hierarchical architecture), autonomous and automated (code is law, community autonomy by stakeholders), organized and ordered (user's rights and organization rules are well specified by smart contracts) (Wang et al. 2019).

Compared with DAOs, traditional online communities are centralized and opaque in governance. The decision-makers have absolute control over governance processes and output (Chen et al. 2021). Although such a structure is efficient in the decision implementation, it requires trust among stakeholders. There are some cases in that decision-makers prioritize self-interest and disregard the benefits of users and stakeholders, which is commonly known as the principal-agent problem (Arrieta-Ibarra et al. 2018; Zhu 2019). Whereas in DAOs, users only need to trust blockchain technologies (e.g., smart contracts) rather than decision-makers. Users govern the communities on behalf of their own perspectives (Ostrom 1990) and this feature is reinforced by the transparency of the technologies. Furthermore, DAOs issue tokens as incentives, which is a remarkable feature that we are interested in.

The token incentive is an important feature and main motivator of DAOs (Tsoukalas and Falk 2020). Each DAO can issue its own tokens and set the operational mechanism. The main goal is to promote user participation and increase general welfare (Wang et al. 2019). So, many DAOs distribute the tokens according to user participation, which means the more users contribute to the organizations, the more tokens they will receive. For example, users (both sellers and buyers) with more trading volume (i.e., the sum of all transactions' value in a certain period) can get more RARI (a token of Rarible) in Rarible (RARIBLE.com 2022); contributors with more content contribution and readers with more user engagement will get more STEEM (a token of Steemit) in Steemit (STEEM.com 2022). Tokens in DAOs integrate the attributes of equity (trade, vote, and long-term value-added), property (the right to some services), and currency (circulating in a specific area). To stimulate users to earn and hold more tokens, most DAOs stipulate that tokens being owned have a direct linkage with voting power and other rights (e.g. discount and no transaction fee) (Messari 2022a).

Hitherto, there is a large body of literature investigating the effect of incentives in traditional online communities such as glory-based incentives (Goes et al. 2016) and financial incentives (Burtch et al. 2018; Kuang et al. 2019). However, the related research about token incentives in DAOs is limited. Because of the unique features of the token incentives, they may, on one hand, encourage users to participate more; on the other hand, they may also induce users to focus too much on financial rewards. The appreciation potential of tokens may lead users to make irrational trading decisions, which may cause false prosperity (users expect too much from token incentives and cost too much to earn them) in the communities. Thus, the effect of token incentives is unclear. As more and more companies are taking attempts on DAO, existing research on incentives in traditional online communities cannot help us determine its effect and provide implications. Therefore, we propose the following research questions. Do token incentives have a positive effect on user participation in online communities? How do they affect the user behaviors of online communities?

In this research, we focus on the context of the Non-Fungible Token (NFT) marketplaces. Specifically, OpenSea is the biggest NFT marketplace created on Dec 20, 2017, which has no intention of issuing token incentives at all (Chapman 2021). On the contrary, launched in Jan 2020, Rarible, which is a rising star in the NFT trading platforms, introduced its governance token RARI on July 15, 2020. The introduction of RARI marked the transition of Rarible from a traditional online community to DAO (Messari 2022b). Another NFT marketplace, SuperRare was created on Apr 20, 2018 (SuperRare 2022b) and introduced its governance token RARE on Aug 17, 2021 (SuperRare 2022a). Therefore, the NFT marketplaces provide us with a unique context to investigate the effect of token incentives by the virtue of a quasi-experiment method.

Utilizing the event that Rarible was the first NFT marketplace that introduced RARI, we investigate the aforementioned research questions at different levels. At the platform level, we investigate the implementation effect of token incentives using the Rarible as the treatment group and SuperRare as the control group. SuperRare is comparable to Rarible in terms of market size and its platform tokens were introduced far behind Raible's (more than one year). At the seller level, because cross-platform trading is possible and OpenSea is the earliest and biggest NFT marketplace, almost all sellers have listed their products on OpenSea for sale. There are only very few sellers who use Rarible as the only channel. Therefore, we take an alternative treatment sample that includes sellers who trade on both OpenSea and Rarible. As for the control group, we focus on only-OpenSea sellers. Such a control group satisfies the exclusion assumption that the behaviors of the individuals in the control group are not affected by the treatment. To address potential self-selection bias due to the freedom of sellers to decide the marketplaces to join, we perform propensity score matching (PSM) for the quasi-experiment design.

Our empirical analysis reveals some interesting preliminary findings. First, token incentives increase platform-level user participation (trading volume and the number of sellers (buyers)) significantly. Second, token incentives stimulate sales (both price and transaction number), which is reflected in sellers selling more at a higher price and buyers buying more also at a higher price compared with the control group. However, by estimating the effect size of token incentives and the equilibrium state analysis, such prosperity is far more than the ideal equilibrium value.

Related Literature

Existing studies have investigated the effects of monetary incentives and their mechanism (Goes et al. 2016; Kuang et al. 2019; Liu and Feng 2021; Wang et al. 2022). However, these conclusions can not give a clear answer to the effect of token incentives. Token incentives in DAOs have some distinct features. First, most online communities are altruism-driven communities, like online review platforms, and online knowledge sharing platforms. In contrast, DAOs are somewhat based on egoism. NFT minters do not contribute and share their works freely, they want to earn more money on the market. Second, token incentives are distributed both to producers (sellers) and consumers (buyers) in most DAOs (e.g., Steemit, Rarible), but monetary incentives in traditional online communities are only given to content contributors. Third, monetary incentives mostly are a reward with a fixed amount of currency, while token incentives have a float value with the fluctuation of the token value. And token amount corresponds to voting power in DAOs (Tsoukalas and Falk 2020). Given these differences between monetary incentives and token incentives, we can not get a reliable inference of the effect of token incentives from the existing research about monetary incentives.

There is also some preliminary research about the effectiveness of token incentives. Thelwall (2018) conducted some basic data analysis which suggests that posts with more sentiment bias and personal information are easier to get more financial rewards than those with more information. Bae and Cho (2019) examined the effect of token incentives in a ride-hailing platform and their preliminary results suggest that token incentives can induce participants and have a greater effect on early users. Zhang et al. (2019) separately investigated the effect of different tokens in Steemit and found that the stable token (SBD) and the vested token (SP) positively affect information quality whereas liquid digital token (STEEM) has no significant impact on information quality.

Based on these studies, we find that existing research about token incentives in DAOs is mainly conducted under the research context of Steemit. And these studies can only suggest the moderating effect of token incentives (Liu et al. 2022) and the differential effects of multiple tokens in Steemit on information quality (Zhang et al. 2019). Moreover, both the two studies focus on the positive side of token incentives. Given more and more communities are paying attention to DAO and token incentives, it is essential to show the causal and comprehensive effects of token incentives on users' behaviors in DAOs and provide guidelines. Therefore, the current work aims to reveal the effects of token incentives from a comprehensive perspective (both positive and negative sides) in the unique NFT marketplace research context.

Hypothesis Development

The motivation theory has been used extensively to explain the effects of incentives in online communities (Kuang et al. 2019; Osterloh and Frey 2000; Roberts et al. 2006). This theory divides motivations into two types: extrinsic motivation and intrinsic motivation (Ryan and Deci 2000). Intrinsic motivation is defined as people contributing something for satisfying their inherent desire. The contribution itself rather than external incentives like some rewards brings them enjoyment and inherent satisfaction. Extrinsic motivation refers to people performing some actions for external incentives like rewards rather than inherent satisfaction (Goes et al. 2016). For our research context, because participants in the NFT marketplace are mainly for-profit, we argue that users' behaviors are driven by extrinsic motivations in the NFT marketplace. Moreover, because of the anonymity in DAOs, the possible crowd-out effect of extrinsic motivations (the introduction of extrinsic motivations reduce the intrinsic motivation of users to participate) may not work in DAOs (Liu and Feng 2021). Egoism is supposed to dominate users' behavior in the NFT marketplace. Therefore, we expect users' participation will be highly activated after the implementation of token incentives. We proposed hypothesis H1:

H1: Token incentives induce higher trading volume and user participation in the NFT marketplace at the platform level.

Considering the external incentives, we anticipate a new supply-demand balance in the market. Based on the supply and demand model (Mankiw 2014), we illustrate the equilibrium analysis as shown in Figure 1. In Figure 1, we define the initial demand curve as D, the initial supply curve as S, and the initial equilibrium point as B. c_o is the initial basic cost of suppliers, and p_o is the initial max price consumers can bear. k_d and

k_s are the slope of the demand curve and supply curve, respectively. According to the definition of elasticity, we assume the range of k_d is (-∞, 0) and the range of k_s is (0, +∞).

When the token incentive policy is implemented, both suppliers and consumers will get some tokens. We define its average value as p_{incent}. Because the incentives make suppliers have lower costs and consumers can bear higher prices, we anticipate the demand curve to move upward and the supply curve to move downward. Both the magnitude they moved is equal to the value of p_{incent}. The new demand curve is defined as D' and the new supply curve is defined as S'. We can get a new equilibrium point B'. c_1 is the new basic cost of suppliers, and p_1 is the new max price consumers can bear. We assume the elasticity of supply and demand does not change, so the slope of the two curves does not change.

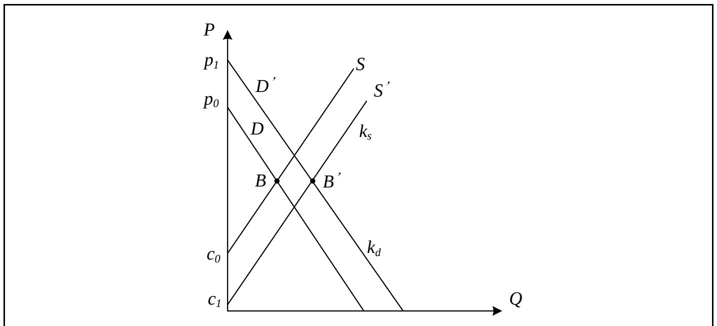

Figure 1. Supply-demand Balance Equilibrium Analysis

Therefore, we can derive the change of quantity and price at the new equilibrium state compared with the initial equilibrium state by analytical solution, which is shown in equation (1). We can conclude the new equilibrium state will see a higher balance quantity, but its magnitude depends on the elasticity of demand and supply and the value of p_{incent}. About the price at the equilibrium state, it could increase or decrease compared with the initial equilibrium state, which depends on the sign of k_s+k_d ($-\infty< k_d <0$, $0< k_s <+\infty$,). According to the range of k_d and k_s, the range of k_d/k_s should be (-∞, 0). We can easily get that the value of ΔP is a monotone increment function of k_d/k_s. Therefore, its value range should be $(-p_{incent}, p_{incent})$. So, we propose hypotheses H2 and H3:

$$\begin{cases} \Delta P = P_{B'} - P_B = \dfrac{(k_s + k_d)\, p_{incent}}{k_s - k_d} = \dfrac{(1+\frac{k_d}{k_s})\, p_{incent}}{1-\frac{k_d}{k_s}} \\[2ex] \Delta Q = Q_{B'} - Q_B = \dfrac{2 p_{incent}}{k_s - k_d} \end{cases} \tag{1}$$

H2: Token incentives lead to a higher transaction number at the new equilibrium state.

H3: The effect size of token incentives on price should be in a limited scope, which is determined by the value of token incentives.

Data and Methods

We collect data from the following sources: Dune Analytics, the user page of OpenSea and Rarible, open API of Rarible. Dune Analytics is a data analysis platform for Ethereum and provides ever-increasing Ethereum data. For our research question, we download the NFT transaction data from Jan 1st, 2020 to Jan 31st, 2021 including the following fields: NFT contract address, NFT token id, transaction time, buyer address, seller address, trading platform, trading price (USD and ETH, respectively). The reasons why we choose this time period are twofold. First, there are no other important functional changes that happened on these platforms during the time period. Second, the governance function of Rarible has not been well established before the end of the time period. There are very few user-proposed proposals. Therefore, we conjecture the observed effect will be mainly driven by the user's evaluation of token value rather than the desire for governance participation.

For the platform-level analysis, we utilize platform-week panel data which contains 56 weeks before and after the event. In terms of dependent variables, we are concerned about the number of all transaction records (*TransNum*), the number of sellers/buyers (*SellerNum/BuyerNum*), the trading volume of all transactions (*TradVol(USD)/TradVol(ETH)*) for platform *i* during week *t*, respectively. *Treat* is equal to 1 for the treatment group (Rarible), and equal to 0 for the control group (SuperRare). *After* is equal to 1 for the post-event period (after the introduction of RARI), and equal to 0 for the pre-event period (before the introduction of RARI).

For the seller analysis, because we want to see the users' behavior change, we only keep the sellers who have transactions before the event date (July 15^{th}, 2021). Under this constraint, we have 12,044 sellers left from our whole data sample. By the virtue of these sellers' addresses, we crawl some data from the user page of OpenSea and Rarible. Specifically, the data from OpenSea user pages includes *user name, user icon, user introduction, social media links, join month*. The data from Rarible user page includes *user name, user icon, user introduction, social media links, following number, on-sale number, liking number*. Additionally, Rarible provides an open API (https://api.rarible.org/v0.1) where we download data about user activities such as *mint history data, bidding history data, and listing history data*.

With these data, we divide sellers into the treatment group and the control group according to whether they have activities in Rarible, respectively. The grouping criteria are whether they have user profile setting (*user name, user icon, user introduction, social media links*), social activities (*following and liking number*), selling activities (*on sales number, listing, and bidding*) on Rarible. If they do not have any of these activities, we can assure that these users do not use Rarible as their sales channel, so they are not affected by the RARI introduction at all. Both OpenSea and Rarible created user pages automatically according to the record on the blockchain, this is the reason that we use actual user activities as the grouping criteria. According to this group criteria, we get 1,831 sellers who have activities both on OpenSea and Rarible (treatment group) and 10,213 sellers who have activities only on OpenSea (control group).

At the seller level, we aim to estimate the average treatment effect of the introduction of RARI on users' trading behaviors. We take cross-platform sellers as the treatment group and only-OpenSea users as the control group. The reason why we do not simply take Rarible users as the treatment group and SuperRare users as the control group is because both of them are small platforms compared with OpenSea, their trading volume at the user level is rare and highly dispersed. However, from the DID estimation of cross-platform vs only-OpenSea users, we can not directly take the trading behavior on Rarible as the dependent variable, because for our control group, the sales on Rarible are 0 in all the observation periods. Therefore, we take all transactions that happened on OpenSea or Rarible, and the transactions that happened on OpenSea, respectively, as our dependent variable. By the comparison of the two estimation results, we can estimate the average treatment effect on the transactions that happened on Rarible.

Specifically, *TransNumAll* and *AvgPriceAll* are the measures of the number and average price of all transactions that took place on OpenSea or Rarible. *TransNumOS* and *AvgPriceOS* are the measures of the number and average price of transactions that happened on OpenSea. All four variables are seller-month panel data. For the independent variables at the seller level, the definition of *Treat* and *After* are similar to platform-level, but the data frequency is set to monthly. For control variables, we control the cumulative platform duration (*AgeOnOpenSea*), the cumulative average price (*CumAvgPrice*), the cumulative mint number (*CumMintNum*), and the cumulative transaction number (*CumTransNum*).

For our research setting, because users independently determine whether to use Rarible, it is necessary to address the potential endogeneity caused by self-selection bias. Thus, we perform propensity score matching before DID estimation. To identify a group of users who are observationally identical to the treatment group except for the treatment condition, we use eight variables constructed as of the day prior to the event day to characterize an OpenSea users' choice of using Rarible. Among them, *UserName*, *UserIntro*, *UserLinkNum*, and *UserIcon* are variables that indicate users' profile information. *UserAgePSM*, *UserMintNumPSM*, *UserTransNumPSM*, and *AvgPricePSM* are cumulative variables that refer to users' duration on OpenSea, total mint number, total transaction number, and average price before the event, respectively.

The DID estimation model we utilized at the platform level is described in equation (2). Because we fix the time effect, the effect of *Treat* will be omitted. Here, we capture the time effect by the coefficient β_1, and the average treatment effect by coefficient β_2. At the seller level, as shown in equation (3), we utilized a two-way fixed effect, so β_1 in equation (3) captures the average treatment effect.

$$Y_{it} = \beta_0 + \beta_1 After_t + \beta_2 Treat_i * After_t + f_i + \varepsilon_{it} \tag{2}$$

$$Y_{it} = \beta_0 + \beta_1 Treat_i * After_t + Control_{it} + f_i + u_t + \varepsilon_{it} \tag{3}$$

Main Results

Platform-level

We got similar trends of these dependent variables between the treatment group and the control group, which support the parallel trend assumptions. Because of the page limit, the figures are not shown here.

Variables	*LogTransNum*	*LogSellerNum*	*LogBuyerNum*	*LogTradVol(USD)*	*LogTradVol(ETH)*
After	0.20**(0.08)	0.33***(0.05)	0.54***(0.06)	1.94***(0.14)	0.98***(0.10)
*Treat*After*	2.90***(0.23)	2.74***(0.17)	2.64***(0.20)	4.04***(0.30)	4.03***(0.28)
R-squared	0.80	0.86	0.85	0.90	0.87

Table 1. Impact of Token Incentive on Weekly User Activities (platform-level)

Note: Constant are omitted here for brevity. *** p<0.01, ** p<0.05, * p<0.1.

Table 1 shows the regression results of the platform level. Compared with SuperRare, the introduction of RARI brings Rarible a significantly higher increment in transaction number (290%), seller number (274%), buyer number (264%), and trading volume (404% in USD and 403% in ETH). According to the statistics, the NFT market boomed in 2021 (Clark 2022). Therefore, the coefficients of *After* are also all positive and significant. The results suggest that, by virtue of the introduction of RARI, the performance of Rarible is beyond that of the same size marketplace in the NFT mania. The findings are in line with other monetary incentive literature. Previous literature has shown evidence that monetary incentives can stimulate user activities (Burtch et al. 2018; Kuang et al. 2019; Roberts et al. 2006). Our hypothesis H1 is supported.

Seller-level

Variables	Obs#	Mean	Std.	Min	Max
TransNumAll	38,064	0.045	0.843	0	86
TransNumOS	38,064	0.037	0.772	0	86
AvgPriceAll	38,064	4.781	195.485	0	29,682.770
AvgPriceOS	38,064	4.299	194.453	0	29,682.770
Treat	38,064	0.077	0.266	0	1
After	38,064	0.5	0.5	0	1
AgeOnOpenSea	38,064	17.666	7.079	0	36
CumAvgPrice	38,064	118.767	791.964	0	34,683.650
CumMintNum	38,064	79.263	605.483	0	18,019
CumTransNum	38,064	6.309	24.829	0	1,136

Table 2. Descriptive statistics of seller-level analysis (after PSM)

The descriptive statistics of seller-level analysis after matching are as Table 2 shows. In our final data set, we have 38,064 observations corresponding to 3,172 sellers, which include 243 sellers in the treatment group and 2,929 sellers in the control group. We draw the parallel trend figure and test the event dynamic effect to test the parallel trend assumption. For brevity, Figure 2 only shows the parallel trends of *TransNumAll* and *AvgPriceAll*. All the results provide evidence for the assumption and show there are no pre-treatment differences between the treatment and control groups.

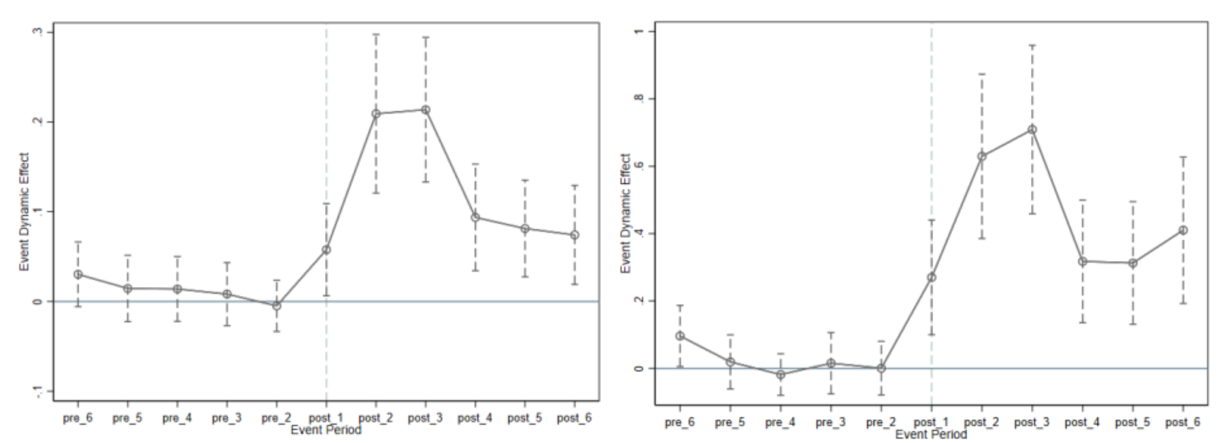

Figure 2. Parallel Trends (*TransNumAll* and *AvgPriceAll*)

Table 3 shows the results of our DID estimation for the impact of token incentives on users' trading behavior at the seller level. We see all positive estimation coefficients of our five dependent variables. That means, compared with its control group, the average treatment effects are all positive. Specifically, compared with only-OpenSea sellers, cross-platform sellers have 11% more transactions number through OpenSea and Rarible, and 6% more transaction numbers through OpenSea. The reasons why OpenSea transactions of cross-platform sellers also increased are as follows: the sales increase in Rarible may release a signal that this seller's NFTs are popular, so the buyers on OpenSea also buy more (spillover effect) from these cross-platform sellers; the price of the same NFT on Rarible and OpenSea must be same, so cross-platform sellers will also raise the price of NFTs on OpenSea. Even though the buyers willing to pay a relatively higher price on OpenSea are not as much as Rarible because of the lack of incentives on OpenSea, few ones will also rise the final average price.

Variables	*LogTransNumAll*	*LogTransNumOS*	*LogAvgPriceAll*	*LogAvgPriceOS*
*Treat*After*	0.11***(0.01)	0.06***(0.01)	0.38***(0.04)	0.25***(0.04)
R-squared	0.27	0.28	0.23	0.22

Table 3. Impact of Token Incentive on User Trading behavior (seller-level)

Note: All control variables and constant are omitted here for brevity. *** p<0.01, ** p<0.05, * p<0.1.

For the effect size of the increment, the growth rate of Rarible sales must be more than 16% ((16%+6%)/2=11%) because the transactions on Rarible are less than OpenSea. So, the hypotheses H2 are supported. Similarly, for the average price of transactions on OpenSea and Rarible, cross-platform sellers are 38% higher than only-OpenSea users. By contrast, cross-platform sellers are only 25% higher than only-OpenSea users for the average price of transactions through the OpenSea channel. That means the growing magnitude of the average price of Rarible sales is more than 51% ((51%+25%)/2= 38%).

Actually, according to the distribution rules and transactions data we get, Rarible distributed 75,000 RARI every week[1] from Jul 15th, 2020 to Jan 31st, 2021 (29 weeks). The total amount of transactions after the event on Rarible is $26,812,836.95. During this period, the average price of RARI is $2.65[2]. Therefore, we can estimate the P_{incent} is 21.50% ((2.65*29*75,000)/26,812,836.95). Because 51% is much higher than 21.5%, we do not find support for hypothesis H3.

Because of the token incentives, sellers raise the price, and buyers are also willing to accept the higher price. But due to the appreciation potential of tokens, people will overvalue the incentives. That phenomenon reflects in the actual equilibrium price (51%) is much higher than it should be (21.5%). Therefore, we argue that token incentives amplified the expectations of users, which induce the actual equilibrium point higher than it should be. It causes false prosperity in the market, overdrawn the spending power of the consumers, and undermines the consumer surplus.

[1]https://rarible.medium.com/introducing-rari-the-first-governance-token-in-the-nft-space-5dbcc55b6c43

[2] https://finance.yahoo.com/quote/RARI-USD/history

We do robustness check analyses focusing on buyers' trading behavior change and conduct heterogeneous timing DID analysis by virtue of all the exact times when each cross-platform user gets their first RARI distribution. All the results still hold, which can have us rule out some exogenous factors.

Discussion and Conclusion

In this paper, we conduct a quasi-experiment in the NFT marketplace research context. We conclude the following key findings. First, we find the positive effect of token incentives on users' participation, which is aligned with the findings of some literature related to monetary incentives (Chen et al. 2019; Kuang et al. 2019) and existing research about token incentives (Liu et al. 2022). Second, as for the effect on users' trading behavior, token incentives can stimulate users so as to achieve a new market equilibrium with a higher transaction number and price. Third, the actual growth percentage of the price is much more than the magnitude it should be. That means such prosperity is based on users' high expectations of token value. We can anticipate that if the token price becomes higher, the users' expectations will become much higher. Therefore, the buyers' trading decisions will always be driven by the high expectations of future token value. And once the token value starts to fail, a rush of selling RARI is likely to happen, and in turn, accelerate the token price decline. To some extent, it is similar to the Ponzi scheme. Eventually, the victim is buyers, they pay a much higher price than that at the ideal equilibrium state.

The current study still has some limitations. For example, because of the limitation of the research context, we can not estimate the effect of the event on Rarible users directly. Therefore, we take the indirect approach for estimating the average treatment effect. That may bring bias to our estimation of the effect size.

Despite ongoing work, this short study has the potential to make important contributions. First, our work contributes to DAO-related research. Existing studies mainly focus on the definition of DAO (Hassan and De Filippi 2021; Wang et al. 2019) and discuss its features in some cases (Beck et al. 2018; Murray et al. 2019). Some works investigated the comparison of the governance structures (Chen et al. 2021) and the effectiveness of token-weighted voting (Tsoukalas and Falk 2020). But the research on the effect of token incentives is limited (Liu et al. 2022; Zhang et al. 2019). Our work is one of the earliest empirical studies which investigate its comprehensive causal effect. This paper also contributes to the stream of research about monetary incentives (Burtch et al. 2018; Kuang et al. 2019; Roberts et al. 2006) with a new form (i.e., token incentives). Moreover, we provide several important practical implications. First, the findings illustrate good examples of the impact of token incentives in DAO, which provide suggestions for managers considering the implementation of DAO. Second, it alerts DAO users of the unreasonably high expectation of the token value and potential bubble bursts in the future. Third, we suggest the regulator of the NFT markets should pay attention to the negative effect of token incentives. False prosperity driven by the token incentives may undermine social welfare considerably.

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