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Tokenized Ownership in Decentralized Autonomous Organizations: Evidence from Steemit

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Completed Research Paper

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Abstract

Decentralized autonomous organizations (DAOs) operate on an incentive network powered by crypto tokens, which are attached with payment rights (i.e., transactional tokens) and ownership rights (i.e., governance tokens). Tokenized ownership is a special incentive way that supports automated operations of DAOs. Our study focuses on this new incentive scheme and construct a quasi-experiment setting to empirically test the incentive effects of tokenized ownership. We find that the intended choice of governance tokens leads to higher post length and readability and higher curation quality compared with transactional tokens. This study contributes to the literature of blockchain and cryptocurrency from an operational perspective and provides practical suggestions for the design of incentive mechanisms in DAOs.

Keywords: Decentralized Autonomous Organization; Crypto Tokens; Ownership

Introduction

Blockchain technology has emerged as a new paradigm to build decentralized systems which do not require a central authority. The potential of blockchain governance is expressed especially through the so-called Decentralized Autonomous Organizations (DAOs). A DAO is an internet-native entity with no central management regulated by a set of automatically enforceable rules on a public blockchain, whose goal is to take a life of its own and incentives people to achieve a shared common mission[i].

Although DAOs can reduce the agency costs resulting from the conflicts of interest between managers and stakeholders (Meckling and Jensen 1976), it has a flaw that not having an owner who, in conventional platforms, would subsidize participation to maximize the platform's network effect (Sockin and Xiong 2023). Another criticism is that when decision-making rights are spread too thin throughout an organization without hierarchy, the efficiency and effectiveness of governance may fail (Morrison et al. 2020). These arguments call for a deep investigation about the efficiency of decentralized ownership.

Decentralized ownership is realized via governance tokens in DAO. Users who have made contributions to the community are awarded governance tokens. Token holders have a say in decisions about new feature proposals and changes to the project's governance system. Having a larger number of governance tokens means more voting power when it comes time to vote. By focusing on governance tokens, we propose our specific research question as whether the reward of governance tokens is a better incentive way for community members than the monetary rewards provided in traditional organizations?

To answer this question has both theoretical and empirical challenges. Theoretically, although the literature on psychological ownership has revealed that employee ownership promotes individuals' positive attitudes and behaviors (Han et al. 2014; Peng and Pierce 2015), the comparison of incentive effects between two profit-sharing schemes, say, ownership and cash, has not been covered yet. DAO is a type of decentralized organization, which provides an ideal setting to observe individual behaviors. By focusing on this virtual community, we extend the literature of employee ownership in corporate management.

Empirically, it is difficult to match users who receive purely governance tokens or monetary rewards on different platforms. We resolve this problem via observing users' choice between governance and transactional tokens in DAOs. The basic rights that tokens confer to holders include transaction and governance, as pointed out by Chod et al. (2022) that tokenized digital platforms are featured by (i) using tokens to settle transactions and (ii) relying on tokens to perform decentralized governance. Accordingly, we focused on the transaction and governance rights of tokens. Governance tokens represent each user's stake in a DAO (George 2022), while transactional tokens, which serve as units of account and are exchanged for goods and services, are cash equivalents[ii]. Using users' choice between governance tokens and transactional tokens, we construct a proxy to measure their preference for ownership or monetary rewards.

We use Steemit, a DAO-type social media platform, as our empirical setting. On Steemit, users are awarded tokens for their participation like blogging and curation. Users can power up to transfer transactional (governance) tokens to governance (transactional) tokens. The power up action is an indicator for users' choice for ownership (monetary) incentives. Employing a matching method, we match two users with/without power up actions and compare their blogging and curation behaviors before and after the power up action. With this PSM-DID method, we find that the decentralized ownership improves the quality of both users' blogging behavior and curation behavior.

The emergence of DAO attracts great attention from the academics (Liu et al. 2022; Zhao et al. 2022). Decentralized ownership is a new incentive way that DAOs create to align members toward collective goals. If the DAO structure incentives well, members are motivated to work and support the community. The decentralized ownership is different from the employee stock ownership plan (ESOP) in conventional organizations. Although prior studies found that employee ownership increases organizational commitment, how the tokenized ownership in an autonomous organization incentivizes users is still unclear. This study is the first one to empirically test the causality relationship between decentralized ownership and user work quality in DAOs, thus enriching the theoretical understanding of corporate management in virtual organizations.

Literature Review

Decentralized Autonomous Organizations

There is a growing tension between digital platforms and their users as online platforms often abuse user rights for profits (Sockin and Xiong 2023). To resolve the conflicts between managers and users, the decentralized autonomous organization emerges as an entity structure in which token holders participate in the management and decision-making of an entity. As a new type of organizational structure, DAOs are different from traditional organizations regarding management and operations, as illustrated in Table 1.

Organizational Structure	**Traditional Organizations**	**Blockchain based DAOs**
Decision Making	Top-down hierarchy (Meckling and Jensen 1976)	Majority consensus (Leonhard 2017)
Management	CEO / board of directors (Meckling and Jensen 1976)	Every stakeholder (Leonhard 2017)
Entity	One legal entity (Hansmann et al. 2003)	No centralized legal entity (Wang et al. 2019)

Contracts	Employment contracts (Baker et al. 1988)	Smart contracts (Morrison et al. 2020)
Incentives	Salary/Stock options, Promotion (Baker et al. 1988)	Cryptographic Tokens (Saito et al. 2019)

Table 1. Differences Between Traditional Organizations and DAOs

While traditional organizations are hierarchically governed by CEOs or boards of directors that follow a top-down hierarchy, DAOs follow a decentralized bottom-up approach. Each member of the organization can submit proposals, which are then voted on by all members. DAO members are typically identified through tokens, which entitle voting rights to the stakeholders to participate in decision-making, thereby coordinating DAO governance. The possession of more tokens typically increases voting power and sometimes tokenized ownership thresholds exist for submitting proposals. The decentralized voting-based governance process reduces the need for hierarchy and bureaucracy, decreasing the need for human managers (Hackl 2021; Morrison et al. 2020). Also, while decision-making in traditional organizations is private, decisions made in DAOs are transparent and publicly visible on the blockchain.

Additionally, blockchain technology shapes the governance of DAOs that are fundamentally different from traditional organizations. These organizations are governed by public and easily accessible blockchain code. The DAO's initial smart contract outlines the goals and governance framework and is irreversible. Any decision made in the DAO should conform to this smart contract, and changes to the smart contract require a voting process. Therefore, the characteristics of DAOs - the overlap between principal and agent, and the strong transparency, significantly reduce conflicts of interest and moral hazard in such organizations. This governance process could constitute a paradigm shift regarding transparency and agency costs (Lumineau et al. 2021).

Finally, distributed and decentralized organizations like the DAOs can benefit from the "wisdom of the crowd" as decision-making power is dispersed among the members of the DAOs. The importance of crowd decision-making is increasingly important in various fields, from the development of new products (Afuah and Tucci 2012), to the financing of technology-based start-ups (Mollick 2014) and scientific research (Franzoni and Sauermann 2014). Crowds have been found to predict events effectively and operate differently than experts (Mollick and Nanda 2016). As such, DAOs represent a natural evolution of crowd-based decision-making platforms.

Incentive Schemes in Online Communities

According to the motivation-behavior literature, user participation in online communities is driven by intrinsic, extrinsic, and internalized extrinsic motivations (Lou et al. 2013). Intrinsic motivations reflect people's own perceptions of the activity as beneficial, because of the passion and enjoyment the activity provokes for them. When intrinsically motivated, a person is moved to act for the fun or challenge entailed rather than because of external products, pressures, or rewards (Ryan and Deci 2000). In extrinsic motivations, rewards or other incentives — like praise, fame, or money — are used to reinforce desired behavior (Khern-am-nuai et al. 2018). External motivation is totally controlled by external forces with the lowest degree of self-determination (Lou et al. 2013). The third type of motivation is internalized extrinsic motivation, which comes from external influences at first and then becomes internalized as ones' own (Ryan and Deci 2002). This motivation is not intrinsic at the outset, but can been assimilated and led to self-regulation (Lou et al. 2013).

As shown in Table 2, most recent studies focused on extrinsic incentives in online communities, such as monetary rewards (Chen et al. 2019a; Qiao et al. 2020; Wang et al. 2022; Yu et al. 2022), social image (Toubia and Stephen 2013), reputation (Lou et al. 2013) and peer pressure from social norms (Burtch et al. 2018). These studies contribute to the design of extrinsic incentive schemes. However, the internalized extrinsic incentive is quite rare in online platforms. To make up this gap, the reward of governance tokens in DAOs provides an ideal setting for studying the internalized extrinsic incentives. Although governance tokens are distributed among contributors as extrinsic rewards at first, the attached ownership gives rise to users' psychological ownership and stimulates their internalized motivations to contribute as an owner.

Regarding to online behaviors, users' posting behavior is intensively investigated. Although curation (or upvote) is critical for community members as a way to identify high quality contents, it is seldomly awarded. In DAOs, curation is a basic decision-making mechanism at the organizational level, and this behavior participants in reward distribution (Zhao et al. 2022). To understand how curation behaviors are incentivized contributes to the related literature.

Author	Incentives	Motivations	Measurement	Behavior
Zeng & Wei, 2013	Social relations	Intrinsic	Quality	Post
Toubia & Stephen, 2013	Intrinsic pleasure, Social image	Intrinsic, Extrinsic	Quantity	Post
Burtch, Hong et al. 2017	Monetary rewards, Social norms	Extrinsic	Quantity, Quality	Post
Khern-am-nual, Kannan et al. 2018	Monetary rewards	Extrinsic	Quantity, Quality	Post
Chen, Hu et al. 2019	Monetary rewards	Extrinsic	Quantity, Quality	Post
Qiao et al, 2020	Monetary rewards	Extrinsic	Quantity, Quality	Post
Wang et al, 2022	Monetary rewards	Extrinsic	Quantity, Quality	Post
Yu et al, 2022	Monetary rewards	Extrinsic	Quantity, Quality	Post
Our Study	Token rewards	Internalized extrinsic	Quality	Post/ Curation

Table 2. Literature of incentives on social media

Ownership Incentive in Corporate Management

Ownership is an incentive way in corporate operations, where employees were granted company shares through employee stock ownership plans (ESOP). Typically, ESOP is part of a compensation package, where shares will vest over a period of time. ESOPs are designed so that employees' motivations and interests are aligned with those of the company's shareholders. In corporate management, the literature revealed two controversial effects of ESOP on firm performances. The positive opinions argue that ESOP improves the firm-level productivity (Kim and Ouimet 2014), revenue (Sesil et al. 2007) and innovation (Chang et al. 2015) as it reinforces the mutual monitoring and cooperation (Hochberg and Lindsey 2010) and create a social exchange relationship (Cappelli et al. 2020). On the other hand, the negative opinions think ESOP has zero or negative incentive effects (Matolcsy et al. 2012) because reward is based on joint performance improvements and individual employees will take a free-riding strategy (Oyer 2004).

Like traditional companies offering ESOP, DAOs offer governance tokens as a form of compensation. DAOs revolutionize corporate management by distributing control and decision-making ability amongst a network of entities, rather than a single controlling entity. Compared to ESOP, governance tokens ensure a broader, distributed ownership and a more flexible exchange scheme. Every community member can obtain governance tokens based on his/her contribution, and token holders can sell their governance tokens at any time. This decentralized ownership is new to online community users and deserve attention for inspection.

Data and Variables

Steemit—A DAO-type Social Media Platform

Steemit is the first blockchain-based social media platform launched on July 4, 2016, allowing users to earn rewards via crypto tokens for posting, curating, and commenting. Different from conventional social media platforms, in which the revenue is generated based on users' traffic and value and belongs the owner of the platform, Steemit works in its own way of token generation, distribution and transaction, and the revenue belongs to every user of the platform. Therefore, Steemit was a typical DAO-type social media platform. Till the end of 2019, there were over 1.3 million users on Steemit. The platform was acquired by Justin Sun on February 14, 2020 through controlling the bulk of tokens. This event centralized the blockchain as one person began to control the platform. Thus, we avoided the shock by focusing data before 2020.

As a blockchain-based blogging website, Steemit is a place for individuals where they can create content, promote the content they deem good, and comment on others' stories. Steemit doesn't have a real owner who would subsidize user participation to maximize the platform's network effect, the platform relies on token allocation to encourage user participation. Users, i.e., content creators and content curators, in this community are rewarded by crypto tokens. All data generated by users are stored in the blockchain.

There are three types of purpose-driven tokens to support the autonomous operation of Steemit platform, i.e., Steem, Steem Power (SP), and Steem Dollar (SBD). Steem is the basic token, which is generated by the blockchain and tradable on external crypto exchanges with a volatile price. Steem Dollar is a stable coin, which anchors the U.S. dollar. In its initial design, 1 SBD should equal to $1 in the long term, but in the short term, SBD price fluctuates if there exists extreme unbalance between supply and demand. Given the fluidity of Steem and SBD, we consider the two transactional tokens as cash equivalents because they can be easily exchanged to U.S. dollars on crypto exchanges.

Similar to the equity issued in traditional firms, Steem Power is a governance token and represents an ownership right in the community. The more SP a user holds, the more weight the user's votes count. In addition, as an ownership right, SP guarantees dividends. In Steem blockchain, 10% of the new Steem coins are paid to the witnesses, while the other 90% of the coins are awarded to content curators, producers and SP holders.

Unlike Steem and SBD, SP is not tradable on external exchanges. However, SP and Steem can convert to each other via power down and power up through built-in wallet on Steemit, with an exchange rate of 1:1. The power up is effective immediately, but the power down takes 13 weeks. Therefore, SP has low liquidity and is a type of long-term investment coin.

Two major ways for Steemit users to retrieve tokens are through blogging and curation. For a blog, the author receives 50% of the total payouts and the curators receive the other 50% of the payouts. The amount of the payouts is determined by the curators' holdings of SP within a 7-day voting window. The platform empowers every stakeholder to apply their knowledge and determine which blog has good content, hence should be rewarded. As the result, the reward pool, the stake-weighted mechanism of influence power to distribute the reward, the independent knowledge of the individuals to determine good or bad content, all put together form an effective way of organizational autonomy. This evaluation mechanism is a group decision making process which reflects the "crowd wisdom".

Data and Variables

Data Collection

All the data on Steemit are stored in Steem blockchain and accessible to the public via the portal of Steem Blockchain Data Service: developers.steem.io. It thus facilitates us retrieving information. We chose the examining period from May 2017 to April 2019, avoiding the acquisition event happened in February 2020. We downloaded all blogs under the "life" tag, because it is the most popular tag used by over 20% of blogs. We totally got 4 million blogs. For each blog, we collected its author name, blog content, post time, upvotes list, blog tags, etc. By using author name, we further retrieved author information, including their transaction history, author rewards history and curation rewards history as illustrated in Figure 1 (b)-(d). We collect data for 98 thousand authors. Users' power up and power down actions can be found in their transaction records. In order to explore users' curation behavior, we further collected information based on their curation history. We found each blog the user upvoted on and downloaded the blog information, including author name, blog content, post time, upvotes list, and blog tags.

Variable Construction

Blogging Behavior

We measure one's blogging behavior from two aspects: text representation and topic interest (Schiefele 1996). Text representation is related to blog quality, which is an important measure for evaluating how much effort one puts in writing blogs. Following prior literature, we measure text representation based on linguistic features, including the word number and readability (Khern-am-nuai et al. 2018). For a textual document, topic analysis is often used to understand content semantics. Shin et al. (2020) proposed that topic complexity and topic consistency are two important measures for capturing blog content. Following their method, we conduct topic analysis and construct two measures to evaluate topic interest. We explain the definition of each variable in the following.

Blog Length measures the number of words in a blog. Text length is the most intuitive measurement of effort since longer text certainly takes more effort (Godes and Silva 2012; Liu et al. 2018). It has been used widely in research related to social media communities to assess users' contribution.

Blog Readability measures the cognitive load needed by a reader to comprehend a blog (Martinc et al. 2021). Traditional readability measures focused on lexical and syntactic features expressed with statistical measurements, such as word length, sentence length, and word difficulty[iii] (Davison and Kantor 1982). These approaches have been criticized because of their reductionism and weak statistical bases (Crossley et al. 2017). With the development of NLP techniques, high-level textual features are explored for readability modeling.

Following the literature (Shin et al. 2020), we measured blog readability via the predictability of a given sentence, that is, how easily a reader can follow each sentence in a blog post. First, we used the pre-trained Google BERT language model to calculate each word's probability given the neighboring words in the sentence (as indicated in Equation 1). Then we calculated perplexity of the sentence based on the probability of each word to evaluate how well the language model predicts the sentence (as indicated in Equation 2). A low perplexity value implies that the sentence is likely to appear based on the neighboring words, and a sentence with a high perplexity value would be less expected for the reader in the current context. Martinc et al. (2021) showed a negative correlation between the perplexity and readability. Thus, we finally used the inverse value of a blog's average perplexity on each sentence as the readability of a blog (as indicated in Equation 3).

$$\log P(w) = \sum_{i=1}^{s} \sum_{j\neq i, j=i-b}^{i+b} \log P(w_j|w_i) \quad (1)$$

$$Perplecxity(s) = P(w_1 w_2 \dots w_s)^{-\frac{1}{s}} = P(w_1)^{-\frac{1}{s}} P(w_2)^{-\frac{1}{s}} \dots . P(w_s)^{-\frac{1}{s}} \quad (2)$$

$$Readability = \frac{1}{n} \sum_{i=1}^{n} perplexcity\ (s) \quad (3)$$

As illustrated in Equation (1) ~ (3), P(w) measures the probability of word w in a sentence. There are totally s words in a sentence and n sentences in a blog.

Topic Complexity measures how many topics that a post covers. Following Shin's approach (2020), we employed the latent Dirichlet allocation (LDA) topic modeling approach to calculate the topic distributions for each blog. The underlying assumption of the LDA model is that a document consists of a small number of latent topics and that the words in the document are the realization of its underlying topics (Blei et al. 2003). Using the trained model, we determined that our blogs are best represented using 10 topics by comparing the perplexities of models with different number of topics. Then we used the LDA model to transform each blog into a 10-dimensional topic vector. Based on blog-level topic distributions, we computed each blog's text complexity at the topic level. Blogs covering multiple topics can be considered semantically complex, whereas those focusing on one or two topics can be considered semantically simple. We define the topic-level complexity for each blog as the Shannon index, where $p(Topic_i)$ is set to be the topic distribution for a given blog, yielding larger complexity values for more diverse topics.

$$TopicComplexity = -\sum_{i=1}^{d} p(Topic_i) \log p(Topic_i) \quad (4)$$

Topic Consistency measures whether an individual blog is similar to or distinct from the usual or average content of blogs (Shin et al. 2020). This index is also calculated based on the topic model. We set $c_i = (p(Topic_1), p(Topic_2), \dots p(Topic_{10}))$ as the corresponding topic distribution computed via the LDA for blog i. This topic vector is compared with the average topic vector for all blogs published on the same day as when blog i published. Then, we measure the topic consistency of blog i using the cosine similarity between c(i) and c(avg) as shown in Equation 5. The value ranges from 0 to 1, with larger values for more popular topics in a blog.

$$TopicConsistency = CosineSimilarity(c_i, c_{avg}) = \frac{c_i \cdot c_{avg}}{\|c_i\| \|c_{avg}\|} \quad (5)$$

Curation Behavior

Curation Leadership measures how a user's curation is leading other users' curation opinions. Opinion leader is defined as "the individuals who [are] likely to influence other persons in their immediate environment." (Katz and Paul Felix 1955, p3) They are often recognized as the early adopters for new ideas in the "diffusion of innovations" model. Based on the definition, we construct the leadership measure. For each upvote made by a user, we calculate the number of upvotes received after the user's upvote divided by the number of total upvotes received by the blog as illustrated in Equation 6. A higher value shows that the user has a good judge of talent and has bigger influences on other users' opinion.

$$CurationLeadership = \#upvotes\_received\_after / \#upvotes\_received\_total \qquad (6)$$

Curation Integrity measures how likely a user upvotes based on blog quality. According to the literature (Tang et al. 2022), user collusion behavior exists in blockchain systems. One is group voting and the other one is vote buying. In group-voting collusion, users A and B vote for each other, whereby both users' token revenue is increased through "reciprocity." In vote-buying collusion, user A votes for user B, who transfers money to user A. Because it is difficult to distinguish group-voting collusion from normal social interactions between users, we only focused on vote-buying collusion. We calculate the ratio of non-collusion upvotes to total upvotes that made by a user as a measure for curation integrity.

$$CurationIntegrity = 1 - \#upvotes\_made\_buying / \#upvotes\_made\_total \qquad (7)$$

Empirical Models and Results

Since our aim is to examine the causal relationship between decentralized ownership and user behavior, a randomized treatment on ownership is expected. But in reality, both governance tokens and transactional tokens play important roles in DAOs. It is quite difficult to find a group of users who hold only governance tokens and another group of users who hold only transactional tokens. To tackle this issue, we focused on the power up action, which indicates a user's preference for governance tokens. After one-time power up, users convert some amount of Steem to SP immediately. By mapping a treated user with power-up action with a controlled user without power-up action, we construct a quasi-experimental setting. We explain our identification strategies and discuss the endogeneity concerns of self-selected responses in this section.

Causal Identification Strategies

When comparing users with and without power-up actions, we assume that power up is an arbitary choice for users. But in fact, users may be affected by many factors in making a power-up decision. These factors can be observable (e.g., users' experiences on the platform) and unobservable (e.g., users' preferences for ownership). To eliminate the heterogeneity caused by observable factors, we first created a "proper" control group for treated users by using propensity score matching (PSM) developed by Heckman et al. (1997). For each treated user, we chose a matched control user with the most similar characteristics. The control group obtained through PSM will be as similar as possible to the treatment group on the observed characteristics.

To further resolve the possible selection bias caused by unobservable factors, the second identification strategy we employed is the difference-in-difference (DID) model. DID estimates the difference before and after a power-up action between two groups of users -- the treatment group (i.e., users with power up) and the control group (i.e., users without power up). With DID, even if treated users are different from control users in important unobserved characteristics, as long as such differences are stable over time in their influences on user behavior, the two-round differences can eliminate the bias.

Propensity Score Matching

For users in the data sample, we firstly identified treated users. A treated user is defined as the one who made his/her first power up in the examining period, i.e., from May 2017 to April 2019. We defined the first power up time as the shock time and make sure there are no power down behaviors 30 days' before and after the shock time. To ensure sufficient observations for users' blogging behaviors, we further required that a user has to publish at least 10 blog posts during the 60 days' observation period. Totally, we have 2,725 users in the treatment group.

For each treated user, we matched the most similar control user based on pretreatment variables, including post number, tenure, reputation score, the strength of social ties, and the amount of SP holding. Post number refers to the total number of blog posts made by a user until time t. Tenure evaluates the number of days from one's registration to time t. Reputation score is a measure provided by Steemit platform which assesses one's ability to obtain rewards. It is determined by the number of upvotes that one user receives and the reputations of the users who gave these upvotes. The strength of social ties is a variable we defined to measure how much support one can get from friends or followers. Because the blockchain system didn't record the time on which one follows another, it is hard for us to get a time-varying follower number. Alternatively, we define a social tie as the following: if user A has 3 upvotes to blogs written by user B, then there is a social tie from user A to user B. The amount of SP holding evaluates one's influence power in the community. All variables are time series, and we used the data on the power-up day for matching. These characteristics make sure that the treated user has no significant difference from the control user regarding to the writing ability, experiences, social ties and SP holding in the community. This is important because these observable characteristics may either influence users' behavior or affect users' decision on power up.

For each treated user, we run a logit regression to predict the propensity scores based on the pre-treatment variables. We then followed Nichol's (2007) approach and used the nearest neighbor method to select a control user with the closest propensity score. Since each treated user has a unique shock time, we repeated the matching process with replacement and obtained 2,725 treated-control pairs. To validate the effectiveness of the PSM, we compared the group mean covariates before and after the matching process. The key goal of matching is to prune observations from the data so that the remaining data have better balance between the treated and control groups (Blackwell, 2009). The verifying result shows that the two groups have significant difference in most of the variables before matching but the difference between the two groups is not significant anymore after matching. Table 3 shows the comparison t-tests, which indicate that all the variables are insignificant at the 5% level.

Variable	t-stat before matching	t-stat after matching
Log(#TotalBlogs)	3.91	0.41
Tenure	2.35	1.13
Reputation	5.91	0.72
Social Ties	3.11	0.95
SP Holding	4.35	0.59

Table 3. Significance of Difference Before/After Matching

Econometric Model and Results

Our implementation of the PSM-DID is illustrated in Figure 1. For each user in the treatment group, the time of his/her first power up is considered as the shock time. For each matched treated-control user pair, we used the shock time of the treated user as the cutoff time for the control user. We observed 30 days' user behavior before and after the shock time (a total of 60 days) for each matched treated-control user pair. To avoid the noisy caused by power down, we confirmed that both treated users and control users have no power down behavior in the 60 days' observing period. In this way, we constructed a staggered DID as shown in Equation 8.

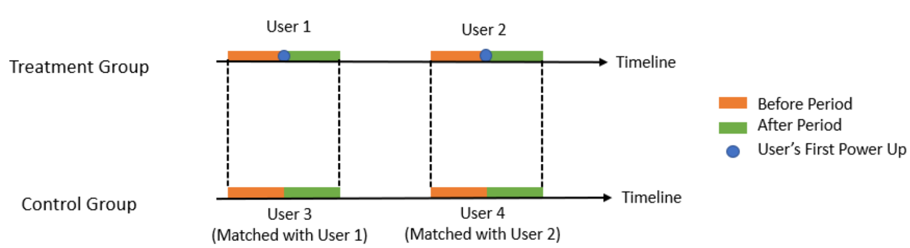

Figure 1. PSM-DID Model

$$DV_{it} = \beta_0 + \beta_1 \times Treatment_i \times Phase_{it} + \beta_2 Controls_{it-1} + \alpha_i + \theta_t + \varepsilon_{it} \qquad (8)$$

where $Treatment_i$ is a dummy variable -- 0 for users in the control group and 1 for users in the treatment group; $Phase_{it}$ is a dummy variable which equals to 0 when time t is before user i's power up action and equals to 1 when time t is after user i's power up action. In addition, we included a group of time-varying variables in the analysis to control for the time-varying confounding factors. The control variables include the number of total blogs posted by a user since his/her registration (Log(#TotalBlogs)), a user's preference for the Life topic (TopicPrefer), a user's ability to obtain upvotes (Reputation), the amount of SP delegation (SP_Delegation) and the amount of SP holding (SP_Holding).

Table 4 reports the estimation results. As shown in columns (1) ~ (4), coefficients of the interaction term $Treatment_i \times Phase_{it}$ are positive and significant on blog length, blog readability and topic consistency, whereas this coefficient is negatively significant on topic complexity. The results indicate that the choice for ownership compensation inspires users to write longer and more easily readable blogs. At the same time, they tend to select a popular topic and focus on the single topic to generate contents.

For curation behaviors shown in columns (5) and (6), coefficients of the interaction term are positive on both curation leadership and curation integrity, showing that the choice for ownership compensation inspires users to make high quality upvotes.

	Blogging				Curation	
Variable	Blog Length (1)	Blog Readability (2)	Topic Comp. (3)	Topic Consist. (4)	Curation Leadership (5)	Curation Integrity (6)
$Treatment_i \times Phase_{it}$	55.31*** (5.67)	0.0085*** (0.0016)	-0.0284*** (0.0043)	0.0274*** (0.0065)	0.0433*** (0.0051)	0.0112*** (0.0027)
R2	0.41	0.30	0.32	0.35	0.33	0.34
Observations	327,000	327,000	327,000	327,000	327,000	327,000

Table 4. PSM-DID Model Results

Endogeneity Concerns of Self-selection

DID Combined with LA-PSM

The PSM-DID model can resolve self-selection problem driven by observable factors and a part of unobservable factors when these factors are time invariant, viz, the differences between treatment and control groups are stable over time. However, the results may still suffer bias if the selection process is driven by unobservable factors which have time-variant influences on user behavior. We address this issue by using a combination of the DID model and the Look-Ahead Propensity Score Matching (LA-PSM) (Kumar et al. 2018).

Users who have used the power-up function (treatment group) might be very different from those users who have never used the function (control group) due to unobserved characteristics. Therefore, the parallel paths assumption may be still violated. To tackle this, we need to construct a better control group which is matched up with the treated group regarding to those unobserved factors. According to Khurana et al. (2019), a better control unit could be a user who has not used the power-up function in the examining period but will use the power-up function in the future.

To implement LA-PSM, we firstly extended our observation period for 30 days to obtain a 90 days' observation period -- 30 days before the power-up day and 60 days after the power-up day. We further split the "after" period into two equally long time periods: time periods 1 and 2. In PSM, for each user in the treatment group, we calculated the user's propensity score on the day of the user's first power-up and match the treated user with a control user who has the closest propensity score on the same day, which ensures that treated and control users have similar observable characteristics. In LA-PSM, we added a restriction that a control user needs to have power up behavior not in period 1 but period 2, which ensures that treated and control users have similar unobserved characteristics. With LA-PSM, we re-estimated our DID model. The results are presented in Table 5, showing consistency with the result in previous section.

	Blogging	Curation

Variable	Blog Length (1)	Blog Readability (2)	Topic Comp. (3)	Topic Consist. (4)	Curation Leadership (5)	Curation Integrity (6)
$Treatment_i \times Phase_{it}$	41.22***	0.0053***	-0.0135***	0.0177***	0.0365***	0.0098***
	(4.38)	(0.0013)	(0.0024)	(0.0045)	(0.0044)	(0.0022)
R2	0.47	0.38	0.35	0.39	0.36	0.37
Observations	170,400	170,400	170,400	170,400	170,400	170,400

Table 5. Regression Results with LA-PSM

Coarsened Exact Matching

For PSM, we estimated the propensity score with logistic regression and use 1:1 matching with replacement. In this method, we assume that all the variables which determined assignment outcomes is independent of any other variables. In other words, our findings are dependent on the function form. In this section, we adopted the coarsened exact matching (CEM) method. CEM is a nonparametric matching method, so it reduces dependences on model. In addition, the treated and control unites are exactly matched based on the covariates in one stratum, which guarantees the balance between matched treated and control units.

By using CEM, we tried different coarsening of strata sizes for every variable representing user characteristics such that treated users and control users fall into the same strata. The matching process produces a vector of weights as output, with unmatched users receiving a weight of 0, treated users receiving a weight of 1, and matched control users receiving a positive weight, showing the strength of the match. We had 1420 treated users in the data sample after matching. Some of the treated users are excluded because no control users fall into the same strata with these treated users. We run the DID model with the matched sample using CEM. As shown in Table 6, the regression results are consistent with results using the propensity score matching algorithm.

	Blogging				Curation	
Variable	Blog Length (1)	Blog Readability (2)	Topic Comp. (3)	Topic Consist. (4)	Curation Leadership (5)	Curation Integrity (6)
$Treatment_i \times Phase_{it}$	41.22***	0.0053***	-0.0135***	0.0177***	0.0365***	0.0098***
	(4.38)	(0.0013)	(0.0024)	(0.0045)	(0.0044)	(0.0022)
R2	0.47	0.38	0.35	0.39	0.36	0.37
Observations	170,400	170,400	170,400	170,400	170,400	170,400

Table 6. Regression Results with CEM

Placebo Effect

We conducted two placebo tests to examine whether our results are driven by chance. One placebo test is on the user level and the other is on the time level. For user-level placebo test, we followed the idea proposed by Bertrand et al. (2004). When randomly generating placebo users and designate them as treated users, if a significant effect at the 5% level is found at a value much larger than 5% of the time, then our analysis could be driven by the placebo effect and the causal relationship between ownership and user behavior doesn't exist. We randomly selected half of the users in the sample and designated them as treated users. We then estimated our DID models and repeated this exercise 2,000 times. We expected to reject the null hypothesis of no causal effect roughly 5% of the time (i.e., 100 times). In our results of the 2,000 runs, we found that the proportion of simulations in which the null hypothesis is rejected is between 3.15% and

3.85% (63 times and 77 times), showing that our results are unlikely to be driven by the placebo effect on user level.

For time-level placebo test, we replaced users' first power-up time with a date that is 15 days earlier. If a significant effect is found, then our results could be driven by factors other than the ownership compensation because users have not yet demonstrated their preference for ownership 15 days prior to their power-up actions. We estimated the DID models using the data with replaced time, and the results in Table 7 demonstrate no significant effects, showing that our results are unlikely to be driven by the placebo effect on the time level.

Variable	Blogging				Curation	
	Blog Length (1)	Blog Readability (2)	Topic Comp. (3)	Topic Consist. (4)	Curation Leadership (5)	Curation Integrity (6)
$Treatment_i \times Phase_{it}$	10.37	-0.0092	0.0020	0.0044	0.0053	0.0082
	(9.66)	(0.0101)	(0.0016)	(0.0055)	(0.0052)	(0.0107)
R2	0.40	0.32	0.33	0.36	0.33	0.35
Observations	302,400	302,400	302,400	302,400	302,400	302,400

Table 7. Results of Time-level Placebo Test

Heterogeneous Treatment Effect

Even though we have controlled for the underlying user characteristics, it is possible that other factors, not the ownership, have caused the changes in user behavior. In that case, the presence and frequency of followed power-ups should not relate to users' blogging and curation behaviors. Otherwise, the multiple presences of power-ups will have multiple incentives to users because we do not expect one power-up to have a lasting effect on all subsequent behaviors.

We argue that the effects of power-up attenuate as time goes by. But when the user performs another power-up, the effects will resume. To statistically test this, we followed prior literature (Chen et al. 2019b) and constructed a variable called SincePU, which measures how many days have passed since the user's last power-up action. For example, if a user performed power-up on May 1st, the variable SincePU on May 1st equals to 0. This variable is set to 1 for May 2nd, and 2 for May 3rd. If another power-up happened on May 4th, the SincePU variable will be reset to 0. We added SincePU in our DID regression and re-estimated the model.

The results in Table 8 show that as time elapses from user's last power-up action, the effects of ownership compensation on users' blogging and curation behaviors begin to decrease. For example, the effects on blog readability decreases for about 0.04% per day. In other words, the effects of power-up will disappear after 23 days (0.0072/0.0004). The effect durations on other behaviors range from 19 days to 73 days. With these results, we can conclude that it is the presence of power-up rather than other unobserved factors that influences user's subsequent blogging and curation behaviors, and the effects of power-up decrease as time goes by.

Variable	Blogging				Curation	
	Blog Length (1)	Blog Readability (2)	Topic Comp. (3)	Topic Consist. (4)	Curation Leadership (5)	Curation Integrity (6)
$Treatment_i \times Phase_{it}$	54.31***	0.0072***	-0.0220***	0.0290***	0.0419***	0.0123***
	(5.34)	(0.0015)	(0.0039)	(0.0072)	(0.0065)	(0.0029)

SincePU	-2.8131	-0.0004***	0.0003***	-0.0011*	-0.0007***	-0.0003***
	(0.2154)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
R2	0.41	0.30	0.32	0.35	0.33	0.34
Observations	327,000	327,000	327,000	327,000	327,000	327,000

Table 8. Results of Heterogeneous Treatment Effects

Alternative Treatment – Power Down

In the main analysis, we used power up as a shock to investigate the impacts of ownership compensation on user behavior. Another research question is whether power down actions, which convert Steem Powers to Steems, have opposite treatment effects.

We constructed our data sample using the same method as in section 4.3. We chose users who had performed their first power-down operation in the observation period as treated users excluding those who cancelled their power downs in 13 weeks[iv]. After PSM, we had 441 users in both treatment and control groups.

Table 9 reports the estimation results. As shown in columns (1) ~ (4), coefficients of the interaction term $Treatment_i \times Phase_{it}$ are negtative and significant on blog length, blog readability and topic consistency, which are in the opposite direction with the power-up treatment. The results indicate that the choice for cash compensation makes users to write shorter and less readable blogs. In addition, they show less willingness to focus on popular topics. For curation behaviors shown in columns (5) and (6), coefficients of the interaction term are negative, indicating that the choice for cash compensation decreases user's upvote quality.

We further compared the magnitudes of the two treatments' effects. The coefficients of power-up treatment (shown in Table 4) are generally higher than the coefficients of power-down treatment (shown in Table 9). For example, a power-up action leads to 55.31 more words in writing blogs, whereas a power-down action leads to 13.34 fewer words in writing blogs. The differences can be explained by the platform's conversion mechanism that power up works immediately while power down takes 13 weeks. A long waiting period will reduce the negative effects caused by choosing the cash compensation.

	Blogging				Curation	
Variable	Blog Length (1)	Blog Readability (2)	Topic Comp. (3)	Topic Consist. (4)	Curation Leadership (5)	Curation Integrity (6)
$Treatment_i \times Phase_{it}$	-13.34***	-0.0091***	0.0021	-0.0176***	-0.0136***	-0.0077***
	(2.28)	(0.0018)	(0.0017)	(0.0035)	(0.0023)	(0.0031)
R^2	0.41	0.31	0.33	0.33	0.40	0.39
Observations	52,920	52,920	52,920	52,920	52,920	52,920

Table 9. Regression Results with Alternative Treatment

Discussion and Conclusions

Key Findings

The decentralized structure and automated operation of DAOs differentiate blockchain-based organizations from conventional organizations. In this paper, we investigate how the decentralized ownership incentivizes users to contribute in DAOs. We focused on two types of user contribution, blogging behavior and curation behavior. We relied on a quasi-experiment setup, in which users' power-up action triggers a shock for the increase of users' ownership shares. We used PSM in combination with DID analysis to rule out users' self-selection issues. Our results show that the intended choice of ownership compensation leads to improved post length and readability. These users like to post on popular and simple topics. The ownership compensation also improves the quality of curation, resulting more influential and integrity upvotes. These results confirm that the decentralized ownership in DAOs effectively motivates users' contribution in the community. Our additional analysis further reveals that the incentive effects attenuate along with the time going, but when the power-up behavior happens again, the incentive effects are reinforced.

The decentralized structure and automated operation of DAOs differentiate blockchain-based organizations from conventional organizations. In this paper, we investigate how the decentralized ownership incentivizes users to contribute in DAOs. We focused on two types of user contribution: post and curation. We relied on a quasi-experiment setup, in which users' power-up action triggers a shock for the increase of users' ownership shares. We used PSM in combination with DID analysis to rule out users' self-selection bias. Our results show that the intended choice of ownership compensation leads to improved post length and readability, but reduced topic complexity. The ownership compensation also improves the quality of curation, resulting in more prescience and integrity upvotes. These results confirm that the decentralized ownership in DAOs effectively inspires users' intrinsic motivation to contribute the community as an owner. Our additional analysis further reveals that the incentive effects attenuate along with the time going, but when the power-up behavior happens again, the incentive effects are reinforced. In addition, a larger relative power-up amount will bring more significant impacts on users' posting and curation behaviors.

Theoretical Implications

By focusing on the decentralized ownership, this paper contributes to the literature in several ways. First, this study enriches the emerging literature of DAOs. The blockchain-based decentralized organization has attracted great attention from the academics. One major literature stream focuses on the financing issues of DAOs, such as initial coin offering (Howell et al. 2020), token value (Sockin and Xiong 2023), speculative trading (Chod et al. 2022), and etc. The other stream investigates the operational issues of DAOs, such as the quality of crowd decision-making (Zhao et al. 2022) and incentive mechanisms (Liu et al. 2022) in DAOs. Our study contributes to the second stream literature. We empirically reveal that decentralized ownership can motivate both users' post and curation behaviors, illustrating a better incentive effect of decentralized ownership than financial rewards. This study inspires future research on strategic design for ownership incentives in DAOs.

Second, this study contributes to the social media literature. Financial incentives are adopted in social media to promote user participation. Prior studies have revealed the effects of financial rewards on post quantity and quality (Chen et al. 2019a; Wang et al. 2022; Wang et al. 2016; Yu et al. 2022). In DAO-type social media, rewards are determined by all community members' upvotes, which asks for high-quality curation behavior. How extrinsic incentives motivate users' upvote behavior is a new research question. Our study finds that ownership will improve users' curation quality, which enriches the literature by revealing the relationship between extrinsic incentives and users' curation behavior in social media.

Third, our study contributes to the area of corporate/organization management. To incentivize employees to work hard, corporate finance has developed governance tools, such as employee stock option plans (ESOPs), through which firms award ownership to employees to incentivize them (Oyer 2004; Pierce et al. 2001). Most literature in corporate finance examines the incentive effects through corporates' financial outcomes at the firm level because individual employee's performance is difficult to observe(Aldatmaz et al. 2018; Kim and Ouimet 2014). In the DAO setting, ownership is awarded to users in a broad range and users' behaviors are easily observed. This study enriches literature via empirically revealing the effects of ownership incentives on individual users.

Managerial Implications

Our study provides several managerial suggestions to the operations of DAOs. First, this study reveals that decentralized ownership has a greater incentive effect on user behavior compared with monetary rewards. This finding confirms that decentralized ownership is an effective incentive way in DAOs. DAO-type platforms should design rules at the operational level to encourage users to hold governance tokens. For example, in Steemit, users would like to hold Steem or SBD for profits when these tokens' price volatility is high. To settle a stable token price is a way to induce users to hold SPs. In addition, some platforms, like Steemit, allow users to delegate their ownership rights to others for profit. This will reduce users' psychological ownership and undermine the incentive effects of ownership. These platforms should consider ban the delegation of governance tokens. Another suggestion is that DAOs can set conditions in smart contracts to encourage users to hold governance tokens for a long time period. For example, the condition may be a minimum holding time to obtain dividends for governance token holders.

Moreover, we find that the power-up action has a decayed incentive effect on users, implying that more power-up actions should be encouraged. It is a proactive way to obtain governance tokens, which has a greater incentive effect than obtaining governance tokens passively from rewards. DAO platforms could consider award users with transactional tokens so that users can proactively convert transactional tokens to governance tokens, which will enhance their psychological ownership and thereby promoting their contributions.

Limitations and Future Research

While giving insights to better understand incentive mechanisms in DAOs, this study has limitations that present future opportunities. First, this study examines the causal inferences between decentralized ownership and user behavior. In order to construct a quasi-experiment setting, we used users' power-up action as a shock to observe the change of users' behavior before and after the shock. However, power up is only one way to obtain governance tokens. Although we tried to compare the incentive effects of governance tokens obtained from power ups and from rewards in surveys, how and why the differences exist are not revealed in this study. A lab experiment is needed to further explore the different incentive effects of different ownership acquirement ways. Second, we used curation leadership and integrity to measure the curation quality. These two variables give some clues about users' efforts and attitudes on curation. More variables are needed to objectively measure the content quality of blogs that are upvoted. Third, this study only focuses on a specific type of DAO —a social media platform. We do not clear that whether the incentive effects of decentralized ownership are different across different DAOs. As the emerging of more and more DAOs, the incentive effects of governance tokens for different tasks could be examined.

Conclusions

This study focuses on the decentralized structure of DAOs and investigates an important issue that how the decentralized ownership incentivizes users to contribute to an organization. We find that the decentralized ownership is a more effective incentive way compared with monetary compensations. Proactive obtaining governance tokens can enhance users' psychological ownership and thereby promoting their contributions. Based on these findings, We propose several practical suggestions about how to effectively design token incentives in DAOs.

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[i] According to twitter.com/licuende/status/1263511552709267456

[ii] https://blog.makerdao.com/the-different-types-of-cryptocurrency-tokens-explained/

[iii] The traditional readability measures include Gunning-Fog Index (FOG) (Gunning 1969), Flesch-Kincaid Reading Ease Index (FK) (Flesch 1951; Kincaid et al. 1975), the Automated Readability Index (ARI) (Kincaid et al. 1975), and the Coleman-Lia Index (CLI) (Coleman and Liau 1975).

[iv] The power-down operation needs 13 weeks to complete.