Voters' Impacts on Creators' Popularity Disparity and Network Size in Two-sided Decentralized User-Generated Content Market

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Abstract

The development of decentralized technologies greatly facilitates the growth of user-generated content (UGC) markets. However, existing literature debates whether the decentralized UGC platform model can be economically sustainable. This study investigates the differential impacts of four voter groups, categorized by their social engagement and financial investment, on the two critical issues pertaining to decentralized UGC markets (i.e., creator popularity disparity and content contribution). We empirically tested our hypotheses using data from a leading decentralized UGC platform. The results indicate a consumer engagement tradeoff between promoting fair growth opportunities in the interest of the creators and extending the creator network in the interest of the platform. Our findings shed light on how creator popularity disparity may arise through votes from the four voter groups and their differential network externalities exerted on the creator network.

Keywords: Voting, Popularity Disparity, Decentralized UGC Market, Long Tail, Content Contribution

1. Introduction

Two-sided user-generated content (UGC) markets offer consumers content sourced from various creators, generate revenue from consumers' consumption, and motivate creators through revenue sharing (Bhargava, 2021). Such markets fueled with content goods (e.g., blogs, videos, recipes, NFTs, etc.) are dominating business and social activities today. Meanwhile, the development of decentralized technologies, such as blockchains, greatly facilitates the growth of UGC markets (Accenture Interactive, 2022; Geng, 2022).

However, the increasing *popularity disparity* - that is, with only a few big winners and many small, powerless players - has held back the growth opportunities for the creators in both centralized and decentralized UGC markets (Jin, 2020). In centralized UGC platforms governed by a single entity (e.g., YouTube), the increasing market power of the top creators creates market inefficiencies. For example, top video creators on YouTube today reportedly earn above six-figure annual incomes, pulling in almost 95% of the platform revenues (Brown, 2021), while over 96% of YouTubers cannot make enough revenue even to surpass the poverty line in the US (Grothaus, 2018). With today's intensified competition among UGC platforms, falling short in providing more equal opportunities for creator growth and financial success are likely to contribute to the market failure of a UGC platform (e.g., the failure of Vine) (Jin, 2020).

The undesirable impact of the increasing popularity disparity may become even more salient to the emerging decentralized UGC markets (e.g., Steemit and HIVE Blog), where creators join the platforms with the expectations of greater autonomy in content monetization without platform interventions (Catalini & Gans, 2020). Such expectations are violated when popular creators are disproportionally rewarded more and gain nearly monopolized market power in decentralized networks. Therefore, understanding the factors that may amplify or impede creators' popularity disparity under the current incentive mechanism of the decentralized UGC market is of great importance.

Decentralized UGC platforms typically implement a *token-weighted crowdsourcing system* to incentivize efficient information aggregation and effortful contributions from platform users to generate high-quality content to benefit the audience (Goldin, 2017). Precisely, a token-weighted crowdsourcing system consists of voting and reward systems. The former crowdsources content preferences through users' votes, where votes from users with more tokens are weighted more in the voting games (Tsoukalas & Falk, 2020). The latter proportionally distributes token rewards to a content based on the total voting weights the content received on the platform (i.e., content reward). The content reward is then shared

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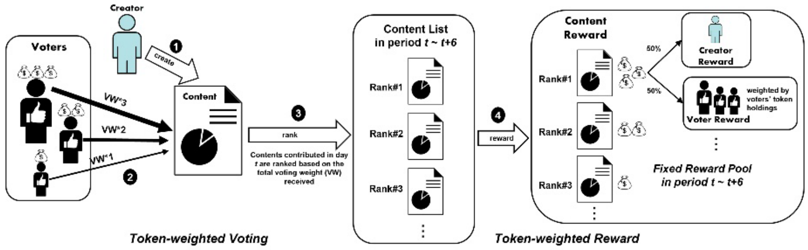

Figure 1. Token-weighted crowdsourcing in decentralized UGC market

between the content creators (i.e., creator reward) and its voters (i.e., voter reward), where the creator receives half the content reward, and the rest is distributed among the content voters proportional to their token holdings (Figure 1). With the token-weighted crowdsourcing system, creators' popularity and thus reward incomes depend heavily on voters' voting choices and voting power on a decentralized UGC platform. Voters may choose to invest in the platform token through purchases or engage in incentivized social activities (i.e., commenting and posting) in exchange for token rewards to increase their voting power.

Socially engaged voters and financially invested voters are likely to have different voting incentives and therefore endorse different voting mechanisms. For instance, on the one hand, socially engaged voters are likely to cast votes with social considerations (e.g., reciprocity) (Song et al., 2019) as their reward payoffs are primarily determined by their incentivized social contributions. On the other hand, voters who proactively invest in the platform token may tend to be fair-minded (Höchtl et al., 2012) in the interest of the platform as their economic payoffs are tied to the market value of the platform (Tsoukalas & Falk, 2020).

Moreover, the network size of active creators is at the core of UGC platforms (Chen et al., 2019). As the theory of two-sided markets predicts (Rochet & Tirole, 2006), the direct interactions between voters and creators are likely to impact users' contribution decisions through cross-side network externalities. Voters' social engagement and financial investment may influence their payoffs and informational externalities (Qiu et al., 2015) exerted on the creator side in the decentralized UGC market (Rochet & Tirole, 2006). Voters who invested in the platform token or are rewarded with tokens for their social contributions (thus with stronger voting power) may produce more substantial cross-side network externalities than voters with little voting power, thus attracting more users to contribute content. Therefore, in this study, we categorize voters into four groups based on their investment and social engagement statuses (Table 1) and examine voters' differential impacts on creators' popularity disparity and network size. Specifically, we ask that in the decentralized UGC market:

RQ1: *How do different voter groups impact popularity disparity among creators?*
RQ2: *How do different voter groups impact creator network size?*

The **contributions** from our findings are threefold. First, prior literature on the long-tail phenomenon has produced mixed findings on whether the transition from bricks-and-mortars to online markets offers small players more opportunities to grow or strengthen superstars' popularity (Anderson, 2006; Elberse, 2008). Our findings contribute to this research stream by considering online consumer heterogeneity in search and evaluation strategies influenced by consumer engagement in the market. Interestingly, our findings suggest that socially engaged content consumers who amplify popularity disparity among creators also attract more creators to join the network, highlighting a potential *consumer engagement tradeoff* between promoting fair growth opportunities in the interest of the creators and extending the creator network in the interest of the platform. Second, our study simultaneously considers online users' social and financial engagement and suggests that voters who engage both socially and financially in an online UGC community are more susceptible to collective opinions (Tsai & Pai, 2021), favoring the 'superstars' in the community. This finding challenges the notion of exposure theory (McPhee, 1963), which suggests that heavy users consume more mixed and niche products compared to the light users. Our findings thus call for a more fine-grained categorization of user engagement rather than the dichotomous approach. Third, the findings from our study also contribute to the literature on two-sided markets, where prior studies primarily focused on the aggregate cross-side network effects on either side of the market (Hinz et al. 2020). Our study suggests that users on the same market side may carry differential cross-side network effects, depending on their financial and social involvement in the online market.

Table 1. Voter categorization

		Socially Engaged?	
		Yes	No
Financial Investment	Yes	Super Voters (SVs)	Pure Invested Voters (PIVs)
	No	Pure Social Voters (PSVs)	Pure Voters (PVs)

The structure of the paper is as follows. We review relevant literature in the next section and theorize our hypotheses in section 3. In section 4, we describe our data and empirical methodologies. We specify our models and summarize the results in sections 5 and 6.

2. Literature Review

2.1. Concerns over Decentralized UGC Market

While there have been efforts to design the decentralized UGC market, concerns such as economic sustainability persist. For example, some scholars are concerned that the token-weighted incentives may encourage more strategic behaviors among users, diminish users' prosocial participatory motivations, and thus affect users' participatory efforts in the decentralized UGC market (Kollmann et al., 2020). However, empirical findings suggest that token rewards may not necessarily cannibalize users' community engagement (Li & Palanisamy, 2019). Social incentives, such as reputation and social connectedness, play equally important roles as pecuniary incentives in driving users' contributions to the market (Liu et al., 2022). Nevertheless, token-weighted incentives may exert differential impacts on users' participatory efforts, depending on users' investment behaviors and social engagement levels. For example, Zhang et al. (2019) and Tsoukalas and Falk (2020) have found that users' token holdings are positively associated with their qualities of content contributions and voting efforts. Prior UGC literature has also indicated that the more engaged users are more likely to commit to and behave in the interests of the UGC communities (Oestreicher-Singer & Zalmanson, 2013). Therefore, it is crucial to consider such users' investment behaviors and social engagement when assessing their participatory efforts.

Another primary concern over the decentralized UGC market is the increasing popularity disparity among creators (Beck et al., 2018), which may lead to the high dependence of the majority on a few "rich" users, compromising the value of decentralization. With the token-weighted crowdsourcing system, decentralized UGC platforms distribute decision rights to the voters on the platform. Hence, voters' voting choices and their political power largely determine the popularity distribution among creators. We address the above concerns by reviewing how popularity disparity may arise in the decentralized UGC market and how voters may vote to impact creators' popularity disparity and network size.

2.2. The Long Tails in Online Market

Our study of creators' popularity disparity closely relates to the literature on the long-tail phenomenon in online markets, where niche products may gain a significant market share as the internet enables consumers to find more of them, reducing the popularity disparity among products (Anderson, 2006; Brynjolfsson et al., 2010). Prior studies have dived into supply-side drivers (Tan et al., 2017), intermediaries' interventions (Lee & Hosanagar, 2019), and demand-side drivers (Park et al., 2020) of the long-tail effects in online markets.

However, the debates over whether online markets enable the long-tail phenomenon remain. Some studies observed that the transition into online markets only offers niche products the exposure advantage in the short run as the networked markets may further strengthen the winning positions of popular products through consumers' observational learning and preferential attachment (Elberse, 2008). Contradictory findings also exist among studies that focused on the effects of intermediaries' interventions on the long-tail distributions of market outcomes. Earlier studies found that implementing recommender systems is positively associated with the long-tail effect in that it increases the market share of niche products in online markets by lowering search costs (Oestreicher-Singer & Sundararajan, 2012). However, other studies suggest a negative impact of recommender systems on the long tail as those systems nudge consumers' choices toward blockbusters in the markets (Lee & Hosanagar, 2019). Studies that focused on the supply-side drivers also produce mixed findings. For example, on the one hand, providing greater variety of products allows consumers to find the products that fit their individual tastes and needs, contributing to the long tail (Lancaster, 1990). On the other hand, the increasing product variety may make adoption choices more complex, leading consumers to use simpler heuristics (e.g., popularity rank), which shortens the long tail (Tan et al., 2017).

These mixed findings can be attributed to consumers' heterogeneities in their search and evaluation strategies. First, even though digital markets have virtually unlimited shelf spaces for more niche products to be displayed, consumers need to be first aware of them through their search. Some consumers are willing to spend more search efforts to reach the products that fit their needs, while others may rely on the popularity-based mechanism, which favors the blockbusters in the market. Therefore, the increase in the former promotes the long tail while the increase in the latter shortens the tail (Lee & Hosanagar, 2019). Second, the long-tail phenomenon may also depend on how consumers evaluate the products. Some may observe others' choices and free ride on others' consumption decisions, breeding popularity disparity among products due to consumers' preferential attachment. Some others may be incentivized to subjectively evaluate products based on their own feelings and experiences, providing niche products fairer chances to be selected and thus contributing to the long-tail phenomenon (Park et al., 2020). In the decentralized UGC markets, the voting mechanisms underlying voters' search and evaluation strategies may influence creators' popularity distribution.

2.3. Content Contribution in UGC Market

Prior UGC literature suggests that creators' content contribution is motivated by three key factors: 1) contribution payoffs, 2) reciprocal norm, and 3) social comparison with others. Creators' content contribution is incentivized by pecuniary and non-pecuniary payoffs derived from their contribution (Kuang et al., 2019). From a two-sided market perspective (Rochet & Tirole, 2006), creators' contribution payoffs are largely determined by the audiences' network effects. Network effects arise when creators derive payoff externalities from each additional user joining the platform (Hinz et al., 2020). Existing literature on the UGC market has generally suggested that the increasing audience network size leads to positive network effects on the creator side (Chen et al. 2019) as it adds tangible (e.g., monetary payoffs) and intangible values (e.g., reputational gains) to the market, thus enhancing the market value to creators (Song et al., 2018). Therefore, in our research context, the payoff externalities derived from voters' participation may impact creators' participation in content contribution.

Creators also contribute content with the expectations of reciprocity from others (Li et al., 2020; Wasko & Faraj, 2005). An online community with a strong reciprocal norm often enjoys a high level of knowledge contribution from its users (Li et al., 2020). Users in such an online community trust other peers will reciprocate their previous favors by recognizing their contribution efforts (Wasko & Faraj, 2005). Xia et al. (2012) have also shown that users made more content contributions when they 'gave more to' an online music community. These previous findings indicate that users are more likely to participate in content contribution with their enhanced confidence of being reciprocated by others through their previous favor-giving behaviors (e.g., upvoting others).

Furthermore, audience is a scarce resource in UGC platforms, and creators need to compete for it (Liu & Feng, 2021). Hence, competitive creators often adjust their contribution behaviors by comparing their contribution efforts and gains with others in the same networks (Bhattacharyya et al., 2020). For example, when facing intensified competition induced by monetary incentives, low-effectiveness creators tend to reduce their contribution efforts due to their aversion to disadvantageous inequity (Tricomi et al., 2010). In a similar vein, inequality in creators' recognition is found to lessen content contribution because popular creators who receive repeated recognition tend to contribute less due to reinforcer satiation, and unpopular creators may also bring down their contribution level to keep a balance between their efforts and gains (Bhattacharyya et al., 2020). To summarize, prior studies suggest that the users' fairness perceptions also play an essential role in determining their contributions in the UGC market.

3. Theories and Hypotheses Development

In this section, we differentiate voter groups based on their social engagement and financial investment considering the token-weighted voting and reward mechanisms in the decentralized UGC market. We theorize voters' differential impacts on creators' popularity disparity and network size based on the voting theories and the literature on UGC contribution.

3.1. How Do Voters Vote?

Conventional theories on voting suggest two value models of voting: the *private value model* and the *common value model* (Borgers, 2004). With the private value model of voting, voters vote their posterior beliefs after observing signals from currently available information without considering other voters' choices. Under such a voting model, voters' preferences reflect their idiosyncratic tastes (Ali & Kartik, 2012). As a result, if voters' tastes are heterogeneous enough, voting with the private value model may contribute to the long-tail phenomenon and reduce the popularity disparity among creators in the decentralized UGC market. In the common value model of voting, voters may vote for what everyone else has voted for because 1) they are likely to take others' votes as quality signals when they are less informed about their voting targets (Callander, 2007), 2) they may conform to the collective preferences under normative pressure (Frey & van de Rijt, 2021), or 3) they tend to vote for the potential winners due to the fear for buyers' remorse (Callander, 2007). Therefore, voting with the common value model may enlarge the popularity disparity among creators as the collective preferences from networked online users would favor blockbusters in the decentralized UGC market.

Literature on cooperation suggests that voters may also vote with reciprocal considerations, termed the *reciprocal value model of voting*, during a repeated voting game (Melamed et al., 2022). Voters may vote with the expectations of others' reciprocal returns or vote to reciprocate previously received votes (Li et al., 2020). Reciprocity that is expected or performed by a voter can be direct or indirect. Direct reciprocity occurs dyadically between a voter and her voting target, whereas indirect reciprocity happens at the network level in which individuals vote highly reputable others or are voted for their reputation (Nowak & Sigmund, 2005). While direct reciprocity is largely motivated by the instrumental value of the reciprocal act (e.g., exchange value), indirect reciprocity is driven by the symbolic value of such an act (e.g., reputation) (Molm et al., 2007). Therefore, reciprocity-oriented voters may favor popular others as they expect to derive great economic and reputational benefits and as popularity often signals reputation of the voting targets (Melamed et al., 2022). Consequently, reciprocity-driven votes may enlarge the popularity disparity among creators in the decentralized UGC market.

Lastly, voters may also be driven by their *fairness motives* and avoid voting for those already popular ones (Höchtl et al., 2012). For example, in a laboratory experiment, Höchtl et al. (2012) observed a fairer income redistribution beyond voters' pocketbook interest (i.e., the redistribution level that maximizes a voter's income) when fair-minded voters in the majority voting are pivotal. Under the *fairness model of voting*, fair-minded voters are likely to contribute to the long-tail phenomenon and narrow the popularity disparity among creators in the decentralized UGC market.

3.2. Voters' Impacts on Creators' Popularity Disparity

Users join the decentralized UGC markets to obtain greater autonomy in content monetization (Catalini & Gans, 2020), and thus different voter groups (see Table 1) in such markets may embrace different voting mechanisms to maximize their reward payoffs. *Pure social voters (PSVs)* are those who participate in incentivized social activities (i.e., posting and commenting) but do not proactively invest in the platform token on a decentralized UGC platform. Their reward payoffs largely come from their social contributions and are closely associated with their social capitals (e.g., reciprocal relations and reputation) on the platform. Hence, PSVs may desire to establish meaningful social relationships that are expected to bring them the most social payoffs. As a result, they may cast their votes under the reciprocal value model concerning direct and indirect reciprocity. They are likely to vote for popular creators with the expectation of greater reciprocal payoffs (i.e., direct reciprocity) and high certainty in the reputation of these creators (i.e., indirect reciprocity). They may also prioritize their reciprocations for popular creators as votes from these creators extend their reward payoffs and reputational gains to a greater extent compared to less popular creators.

Besides, prior studies on user engagement show that information-sharing oriented individuals are most susceptible to social norms in online communities because they care about their impression and desire a shared identity in the communities (Liu et al., 2019). Hence, PSVs who often contribute content on the platform are also likely to follow the common value model of voting and vote for popular content appreciated by the majority due to the normative pressure. For these reasons, we hypothesize that:

H1: *The increase in the number of votes from PSVs enlarges the popularity disparity among creators on a decentralized UGC platform.(reciprocal/common value)*

Pure invested voters (PIVs) are those who proactively invest in the platform token (which requires 13 weeks for an invested voter to completely withdraw the invested token) but do not involve in any other incentivized social activities and thus are not driven by reciprocal benefits. Their payoffs are largely determined by the token value and thus the market attractiveness of the decentralize UGC platform (e.g., acquisition and retention of creators and other users). As PIVs not only stand to benefit more from an increase in the market value of the invested tokens but also bear loss from a decrease. As the prospect theory predicts, the economic loss looms larger than gain (Kahneman & Tversky, 1979). Therefore, PIVs may vote in a way that stabilizes the market and reduces potential loss due to the volatility of the invested tokens (Liu et al., 2022; Tsoukalas & Falk, 2020). In decentralized UGC markets, content consumers are attracted by high-quality and diverse content, while creators benefit from having fair opportunities to grow (Goldin, 2017). Votes from PIVs, hence, are likely to be driven by their private values and fairness motives – that is, they may tend to cast truthful votes based on their assessments of content quality (Ali & Kartik, 2012) and promote high-quality contents that are less popular (Höchtl et al., 2012). Consistent with our argument, prior user engagement literature also suggested that compared to free users, users who have financially invested are also more likely to spend efforts on content searching and consume less popular content in online communities (Oh et al., 2016). Hence, we hypothesize that:

H2: *The increase in the number of votes from PIVs reduces the popularity disparity among creators on a decentralized UGC platform. (private/fairness value)*

Super voters (SVs) are those who not only engage in incentivized social activities but also invest in the platform token. Similar to PIVs, SVs may also concern about the potential loss induced by the fluctuations in the token value. However, unlike PIVs who do not engage in incentivized social activities and thus have no alternative reward income, SVs may offset their investment risks through their social contributions. Therefore, like PSVs, SVs are likely to vote for creators with expectation of their reciprocal returns. Such reciprocal value model of voting would lead to greater popularity disparity among creators as voters tend to vote for the already-popular ones for greater economic and reputational benefits.

Moreover, prior studies have indicated that users who are incentivized by both social and financial benefits tend to participate more in an online community (von Krogh et al., 2012), and deeply engaged users are shown to be more prone to group conformity (Tsai & Pai, 2021) than those who are less engaged. Hence, SVs are likely to vote for popular content that are favored by other voters in the market, following the common value model of voting. We thus hypothesize that:

H3: *The increase in the number of votes from SVs enlarges the popularity disparity among creators on a decentralized UGC platform.(reciprocal/common value)*

Finally, *pure voters (PVs)* are neither socially engaged (i.e., posted or commented) nor financially invested in decentralized UGC markets. Thus, unlike other voter groups, they do not vote with the expectation of others' reciprocal returns or vote to reduce investment risks. Instead, PVs, who are likely to be the least informed voter group due to their lack of engagement, may simply vote for the use value of the content (Zhou et al., 2018). Therefore, we hypothesize that:

H4: *The increase in the number of votes from PVs reduces the popularity disparity among creators on a decentralized UGC platform.(private value)*

3.3. Voters' Impacts on Creator Network Size

In this section, we hypothesize the impacts of the different voter groups on creator network size in decentralized UGC markets based on the literature on online content contribution (see Section 2.3.). We propose that the increase in votes of PSVs and SVs may attract more users to contribute content in decentralized UGC markets for the following reasons. First, both PSVs and SVs are token holders who have voting power in the market. The former may earn token rewards through their incentivized social activities, and the latter also invest to own tokens. Creators' contribution payoffs are largely determined by the number of powerful votes cast in the market and thus the amount of creator reward they may receive. The contribution payoffs also fluctuate with the platform token value in the market, which is driven by users' investment in the token. Therefore, the votes from PSVs and SVs are likely to carry pronounced cross-side network effects, where creators' direct payoffs (i.e., creator reward) and indirect payoffs (i.e., token value) are enhanced with each additional voter in the two voter groups casting votes in the network, attracting more creators to the market (Song et al., 2018). Second, PSVs and SVs may vote with expectations of others' reciprocal returns. Their voting activities may help them extend and reinforce their reciprocal relationships with others in the market (Li et al., 2020; Wasko & Faraj, 2005). Hence, the more votes they cast for others, the higher their confidence in getting voted when they contribute, thus encouraging their future contribution. Concerning the contribution payoffs and reciprocal returns the PSVs and SVs may bring to creators, we hypothesize that:

H5: *The increase in the number of votes from PSVs attracts more creators on a decentralized UGC platform.*

H6: *The increase in the number of votes from SVs attracts more creators on a decentralized UGC platform.*

We propose that votes from PIVs may also encourage more users to contribute content to the decentralized UGC market from two perspectives. From the two-sided market perspective (Rochet & Tirole, 2006), similar to PSVs and SVs, votes from PIVs who hold tokens and have the voting power generate cross-side network effects as creators benefit from the enhanced direct and indirect payoffs from their votes. Also, as argued in the previous section, PIVs may tend to vote for high-quality but less popular creators in the interest of the decentralized UGC platform. From the fairness motive perspective, more new creators may join the network to contribute content after observing fairer opportunities to be paid off (Bhattacharyya et al., 2020). Concerning the contribution payoffs and fairness value PIVs may bring to creators, we hypothesize that:

H7: *The increase in the number of votes from PIVs attracts more creators on a decentralized UGC platform.*

Lastly, we propose that the increase in votes from PVs may have no impact on creator network size because PVs who do not hold tokens may not generate payoff externalities as their votes neither directly contribute to creator reward nor indirectly influence the platform token value.

4. Data and Methodology

We collected data from a leading decentralized UGC platform in the US. The data consists of 16,334,995 upvotes for 256,203 content posts from

January 1, 2022, to February 27, 2022. It captures all the content contribution activities, the voting information for each content, and the information relates to the attributes of creators, voters, and content (e.g., token holdings, reputation scores, number of posts, and comments) during the study period. We categorize a voter as a PV if (s)he neither proactively invested in any platform token nor had any posts or comments since account registration. PIVs are those who invested in the platform token without any posts or comments since the account registration. PSVs are those who engaged in posts or comments but did not invest in any platform token. SVs are those who invested in the platform token and engaged in posting or commenting activities.

Next, we aggregate our data at the daily level. We see the total upvotes received by a creator in a day as the creator's popularity of the day. We then compute the daily creators' popularity disparity using the Gini Coefficient of creators' popularities. The higher the Gini Coefficient, the larger the popularity disparity among creators. We present the summary statistics in Table 2 and the correlation matrix of key variables in Table 3.

Table 2. Summary statistics of key variables (standardized)

Key Variables	**Obs.**	**Min**	**Mean**	**Max**	**SD**
Daily Creators' Popularity Disparity (CPGini)	57	-2.86	0.08	1.46	0.08
Daily Creator Network Size (Creators)	57	-2.06	0.02	4.74	0.99
Daily PVs' Votes (PVv)	57	-1.92	0.05	3.12	0.94
Daily SFVs' Votes (SFVv)	57	-1.39	0.10	1.57	0.67
Daily PIVs' Votes (PIVv)	57	-1.97	0.03	3.64	0.99
Daily SV's Votes (SVv)	57	-1.22	0.10	1.35	0.64
Control Variables	**Obs.**	**Min**	**Mean**	**Max**	**SD**
Daily Average Upvoting Weight	57	-2.15	0.01	2.27	1.00
Daily Average Downvoting Weight	57	-2.11	-0.02	1.93	1.00
Daily Average Voter Token Holdings	57	-2.18	0.04	1.78	0.96
Daily Average Voter Reputation Score	57	-2.49	0.02	1.96	1.00
Daily Token Price	57	-1.38	-0.03	0.99	2.51
Daily Average Content Length	57	-3.95	-0.05	2.00	0.93
Weekend Dummy	57	0.00	0.30	1.00	0.46

Notes: In our research context, not only do users allow to cast downvotes on a content post, but also they can choose the weights of their downvotes, which ranges from 0 percent to 100 percent. The higher the downvoting weights, the more negative impacts their downvotes would have on the reputation of the downvoted creators. We therefore control for the impact of downvoting weights in our OLS models, even though we did not find significant impacts of the downvoting weights on popularity disparity.

Table 3. Correlation matrix of key variables

	CP Gini	**Creators**	**PVv**	**SFVv**	**PIVv**	**SVv**
CPGini	1.00					
Creators	-0.21	1.00				
FVv	0.42*	-0.09	1.00			
SFVv	0.28*	0.36*	0.02	1.00		
PIVv	-0.57*	0.53*	-0.30*	0.16	1.00	
SVv	0.15	0.49*	-0.09	*0.77**	0.27*	1.00

Notes: * p<0.05; two-tailed significance.

5. Model Specifications

We test our hypotheses using ordinary least square (OLS) models and vector autoregression models with exogenous variables (VARX) models. Specifically, we estimate the effects of votes from the different voter groups on creators' popularity disparity using two OLS models as follows. The effects of PSVv and SVv are separately tested in the two OLS models to avoid multicollinearity. All the variance inflations (VIFs) of the independent variables in the two models are lower than 3, indicating that multicollinearity is not a concern in our analysis.

$$CPGini = \beta_0 + \beta_1 PVv + \beta_2 PSVv + \beta_3 PIVv + \beta_4 Weekend + \beta_i Control_i + \varepsilon_1 \quad (1)$$

$$CPGini = \beta_4 + \beta_5 PVv + \beta_6 PIVv + \beta_7 SVv + \beta_8 Weekend + \beta_j Control_j + \varepsilon_2 \quad (2)$$

Moreover, we adopt VARX models to examine the effects of votes from the different voter groups on the creator network size, as VARX model avoids unreasonable assumptions of strict exogeneity and allows us to capture the possible dynamic interactions between the impacts of votes and the creator network size (Adomavicius et al., 2012). To avoid multicollinearity, the effects of PSVv and SVv are tested separately. We follow the standard VARX modeling procedure (Song et al., 2018).

First, we treat our key variables as endogenous and determine their stationarity using the augmented Dickey-Fuller unit-root tests. The test results suggest that all the first-differenced endogenous variables are stationary. Next, we determine the optimal lag based on lag-order selection statistics. The results suggest that the first-order lag is the optimal lag with the lowest Akaike Information Criterion, Hannan–Quinn information criterion, and Structural Bayesian Information Criterion. Therefore, we specify two first-differenced VARX models with one-day lags as follows:

$$\begin{bmatrix} \Delta Creators_t \\ \Delta PVv_t \\ \Delta PSVv_t \\ \Delta PIVv_t \end{bmatrix} = \sum_{j=1}^{p} \varphi_j \times \begin{bmatrix} \Delta Creators_{t-j} \\ \Delta PVv_{t-j} \\ \Delta PSVv_{t-j} \\ \Delta PIVv_{t-j} \end{bmatrix} + \partial_0 Weekend + \partial_1 \Delta Controls_{t-j} + \Delta\varepsilon_t \quad (3)$$

$$\begin{bmatrix} \Delta Creators_t \\ \Delta PVv_t \\ \Delta SVv_t \\ \Delta PIVv_t \end{bmatrix} = \sum_{j=1}^{n} \gamma_j \times \begin{bmatrix} \Delta Creators_{t-j} \\ \Delta PVv_{t-j} \\ \Delta SVv_{t-j} \\ \Delta PIVv_{t-j} \end{bmatrix} + \partial_2 Weekend + \partial_3 \Delta Controls_{t-j} + \Delta\in_t \quad (4)$$

where t is the index of day, j is the maximum number of lag(s) (which is one day in our analysis), and ε_t and $\in_t$ are four-element vector of error terms, which are assumed to be serially uncorrelated when the optimal value of lags j is applied. φ_j and γ_j are 4×4 matrices of slope coefficients for our endogenous variables.

6. Results and Discussion

Overall, both the OLS models and VARX models show good model fits and explanatory power. Largely consistent with our hypotheses, the empirical results show the differential impacts of the four voter groups on both creators' popularity disparity and their network size in the decentralized UGC market. Specifically, the two OLS model results (see Table 4) show that the number of votes from PSVs and SVs have significant and positive impact on the Gini Coefficient of daily creators' popularities, thus enlarging the popularity disparity among creators at the daily level (H1 and H3 are supported). Among the three voter groups, votes from SVs have the largest impact on creators' popularity disparity, followed by PSVs and PVs. Our results also show that votes from PIVs who do not engage in incentivized social activities have a significant and negative impact on the Gini Coefficient of creators' popularity, suggesting that one unit increase in votes from PIVs narrows the creators' popularity disparity by 27 to 28% (H2 is supported). Surprisingly, the increase in the number of votes from PVs, who do not concern about social dynamics and investment risks, is shown to enlarge the popularity disparity among content creators (contradictory to H4).

Table 4. OLS model results (N=57 days*)*

DV: CPGini	**Model (1) (SE)**	**Model (2) (SE)**
PVv	0.29*** (0.08)	0.24** (0.09)
PSVv	0.40*** (0.11)	/
PIVv	-0.28* (0.11)	-0.27* (0.11)
SVv	/	0.55*** (0.15)
Controls	**Included**	**Included**
Adj. R-Squared	**0.60**	**0.59**
Root MSE	**0.49**	**0.49**
Mean VIF	**1.77**	**1.92**

Notes: *SE, standard errors.* *p<0.05; **p<0.01; ***p<0.001, two-tailed significance.

The results can be partially explained by the exposure theory (McPhee, 1963), which suggests that heavy users are more likely to consume niche products, and light users tend to consume popular products. Our results show that votes from PIVs tend to vote fairly and narrow the creators' popularity disparity, while PVs may be more likely to free ride on or herd with others' voting decisions and thus amplify the creators' popularity disparity. However, our results also indicate that heavy users (i.e., SVs) who engage both socially and financially in the decentralized UGC markets may be the most susceptible to collective preferences due to the normative pressure due to their frequent engagement in impression management (Tsai & Pai, 2021). Besides, SVs may also be the most influential voters whose votes are likely to guide others' voting decisions and lead to positive feedback loops, which further enlarge the popularity disparity among creators. The results call for a more fine-grained categorization of user engagement rather than the dichotomous approach between heavy and light users.

Moreover, our first-differenced VARX model results (see Table 5) show that the increases in votes from PSVs and SVs in day *t-1* are positively associated with the increase in creator network size in day t, whereas the increases in votes from PIVs and PVs in day *t-1* do not significantly influence the growth of creator network size in day *t.* Therefore, H5, H6, and H8 are supported, and H7 is not supported. We further plotted the cumulative orthogonalized impulse response functions (COIRFs) for the daily variations in the impacts of votes from PSVs and SVs on creator network size in the following day (see Figure 2). The COIRFs show that the cumulative increases in votes from the two voter groups have the most significant positive impacts on the creator network size one day after the shocks, and the cumulative positive impacts sustained for at least 20 days. We conducted several robustness checks, including a stability test, autocorrelation test with Lagrange-multiplier test, and Granger Causality Wald tests. The results show our VARX models satisfy stability conditions, no autocorrelation at lag order, and Granger causality test results are consistent with our VARX models.

Our findings through VARX models add additional insights into the impacts of the SVs and PSVs. The findings suggest that despite the fact that the votes from the two voter groups significantly enlarge the creators' popularity disparity, their votes also contribute to the increase in creator network size in the decentralized UGC market. These positive impacts on creator network size may be attributed to the payoff externalities and informational externalities the voting outcomes of the two voter groups brought about. The results indicate a consumer engagement tradeoff between promoting fair growth opportunities in the interest of the creators and extending the creator network in the interest of the platform.

Table 5. First-differenced VARX model results

Response: ΔCreators$_t$	**Model(3)**	**Model(4)**
Δ*Creators*$_{t-1}$	-0.64*** (0.11)	-0.66*** (0.11)
Δ*PVv*$_{t-1}$	-0.18 (0.14)	-0.19 (0.15)
Δ*SFVv*$_{t-1}$	0.60*** (0.15)	/
Δ*PIVv*$_{t-1}$	0.11 (0.14)	0.18 (0.14)
Δ*SVv*$_{t-1}$	/	0.78*** (0.23)
ΔControls$_{t-1}$	**Included**	**Included**
R-Squared	**0.56**	**0.52**
Root MSE	**0.75**	**0.77**

Notes: SE, standard errors. * p<0.05; ** p<0.01; *** p<0.001, two-tailed significance.

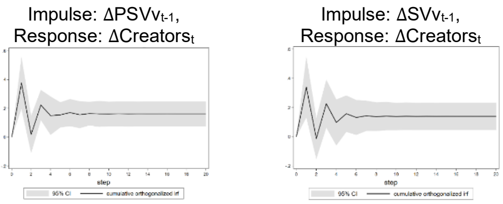

Figure 2. COIRFs

7. Conclusion and Future Research

In this paper, we theorize voters' differential impacts on creators' popularity disparity and network size in the decentralized UGC market powered by token-weighted crowdsourcing mechanisms. Using the data from a leading decentralized UGC platform, we empirically test our hypotheses using OLS and VARX models. Our findings largely support our hypotheses. The findings shed light on how creators' popularity disparity may arise or be suppressed through votes from socially and financially engaged voters in the market. Our findings also suggest the differential network externalities of the different voter groups exerted on the creator network.

Our research can be extended in three directions. First, our theoretical framework can be extended by more comprehensively integrating theories on voting, the two-sided market and the long-tail effects to examine additional voting incentives. Second, the empirical analysis can be extended to multiple UGC platforms with longer sample time frame as the impact of fairness perception may vary across platforms and over time. This allows researchers to examine whether the findings obtained in this study exist on other platforms and what the long-term impacts of our findings are on platform sustainability. Last but not the least, as voters in one voter group are likely to be converted into another voter group over time, the current study may also be extended by taking into account such evolutionary dynamics.

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