Unexpected Monetary Incentives and User-Generated Content on Digital Platforms

Short Paper

Florian Pethig
Tilburg University
Tilburg, The Netherlands
f.pethig@tilburguniversiy.edu

Hartmut Hoehle
University of Mannheim
Mannheim, Germany
hoehle@uni-mannheim.de

Kai-Lung Hui
Hong Kong University of Science and Technology
Clear Water Bay, Hong Kong
klhui@ust.hk

Andreas Lanz
University of Basel
Basel, Switzerland
andreas.lanz@unibas.ch

Abstract

Many digital platforms offer monetary incentives to encourage user-generated content. While the effectiveness of piece-rate schemes (e.g., pay-per-review) and linear pay structures (e.g., pay-per-view) has been extensively studied, research on relative performance schemes is limited. In this paper, we leverage proprietary data from deal-sharing platforms that introduced a tournament-like relative performance scheme by rewarding contributors who posted the highest-voted contribution per day in each main category. This scheme was not publicly announced; contributors learned about it only after winning for the first time. Our results show that after receiving the reward, contributors become more active in posting deals and voting on others' deals. However, they strategically exploit their knowledge by withholding upvotes and increasing downvotes on other deals posted in the same category as their incentivized deal.

Keywords: Digital platforms, user-generated content, monetary incentives, user behavior, regression discontinuity design, difference-in-differences

Introduction

Digital platforms often use monetary rewards to incentivize the production of user-generated content (UGC). Because the sheer volume of UGC strains users' capacity to discover contributions that merit their attention, platforms seek to elicit high-quality contributions from their users. Several incentive schemes condition the rewards on the relative quality of contributions. To determine contribution quality, platforms typically consider the number of upvotes, or helpfulness votes assigned by other users. For example, as part of Amazon's "Vine Club" incentive scheme, a select group of users receives free products in exchange for a review. The exact criteria by which Amazon selects members for the Vine program are not publicly available, but Amazon indicates that it relies on the helpfulness of previously written reviews. Essentially, the Vine program is a relative performance incentive scheme, where only the best-performing users are admitted to, and stay in, the Vine program.

The effectiveness of piece rate schemes (e.g., pay-per-review; see Burtch et al., 2018; Khern-am-nuai et al., 2018) and performance-contingent schemes with linear pay structure (e.g., pay-per-view; see Balbuzanov et al., 2019; Chen et al., 2019) as incentive schemes have been extensively studied in the literature. However, there is limited research on how digital platforms can design relative performance schemes to incentivize users. In this paper, we examine a tournament-like relative performance scheme that relies on the rank order of contributions based on the net score of up- and downvotes assigned by other users of the platform.

Rank-order tournaments exist in academia, crowdsourcing, sports, and many other contexts, where "individuals and teams [are] being measured against one another in pursuit of a reward" (Casas-Arce & Martinez-Jerez, 2009, p. 1306). Empirical and theoretical work suggests that tournaments have unique properties that could make their implications for stimulating UGC non-trivial (e.g., Casas-Arce & Martinez-Jerez, 2009; Lazear & Rosen, 1981). On the one hand, tournaments typically disproportionally reward the best-performing users. Tournaments can thus help platforms strategically entice power users. Tournaments also eliminate common shocks that affect users' performance, such as a low number of visitors to the website. Thus, they may incentivize users to post on less busy days, which could ensure a steady stream of UGC. On the other hand, tournaments may increase the competition among users with potentially unintended negative effects: as users produce their own and evaluate others' contributions, tournaments may incentivize suppressing competitors' performance and thereby increasing their own chances of a higher position in the ranking (Harbring & Irlenbusch, 2011). Such competitive behavior can distort the ratings on digital platforms, making it more difficult to assess the "true" quality of the contributions.[1]

Consequently, an important question for platforms that use tournament incentive schemes is how these schemes affect the contributions and behaviors of different types of users. This study aims to address the following questions: Does awareness of a tournament incentive scheme distort user behavior? How do tournament schemes impact different types of users, such as those driven by intrinsic versus extrinsic motivation? To what extent should platforms rely on tournament schemes to incentivize user engagement?

We address these questions empirically by leveraging fine-grained, longitudinal data spanning over eight months from three deal-sharing platforms in Europe. On these platforms, contributors post deals and vouchers, which are upvoted or downvoted by other users. In September 2021, the platforms started to award contributors who posted the deals with the highest net score of votes per day in one of the main categories (e.g., electronics, home and living) a 10 EUR voucher. The incentive scheme in our setting therefore exhibits the properties of a tournament: receiving the voucher is not contingent upon the output level but conditioned on "winning", i.e., posting the highest voted contribution of the day.

An important feature of our setting is that the incentive scheme was not publicly announced by the platforms. Instead, recipients were informed via direct messaging by the platforms, who disclosed the reward and the rules of the scheme. Thus, the scheme endogenously sorted users into *informed users* who could compete in future tournaments and *uninformed users* who remained unaware of the scheme. The unexpectedness of our setting offers unique advantages for causal inference: (1) the setting fulfills the no-anticipation assumption, which states that the treatment has no causal effect prior to its implementation (Roth et al., 2023), and (2) it helps ensure our setting fulfills the stable unit treatment value assumption (SUTVA), because uninformed users are unaware of the incentive scheme and, therefore, should have no intention to compete for the rewards (Eckles et al., 2017).

Once we have completed the empirical analysis, we expect to make the following contributions. First, this study establishes the impact of tournament incentive schemes on UGC, particularly in how adding a tournament to digital platforms affects the behavior of informed and uninformed users. Prior research on monetary incentives primarily focuses on incentive schemes with linear pay structures (e.g., pay-per-review or pay-per-view). There exists limited empirical evidence beyond laboratory studies (see Dorner et al., 2020) to conceptualize how users change their behavior when they unexpectedly receive a reward and thus information about an incentive scheme that encourages them to perform *relatively better* than other users.

Second, we advance research on the competition among users, a topic rarely studied in the literature (Liu & Feng, 2021). Shen et al. (2015) find that Book reviewers on Amazon are sensitive to the competition among existing reviews and try to avoid crowded review segments. Huang et al. (2015) show that employees on an enterprise blog platform increase postings as competition decreases. Here, we study the strategic decisions of informed users before and after they learn of a relative performance incentive scheme. We plan

[1] Anecdotal evidence in Dorner et al. (2020) indicates that after the introduction of Amazon's Vine program, members complained that their reviews received a substantial number of downvotes. Members suspected that fellow reviewers were strategically downvoting their reviews to replace them as Vine members, or to protect their own membership status. Even after Amazon removed the possibility to downvote reviews in 2018, reviewers were still able to improve their chances of remaining in the Vine program by refraining from upvoting reviews written by others.

to uncover how different competitive behaviors in tournaments on digital platforms emerge, including those that are directed at increasing one's own performance vs. diminishing others' performance.

Third, this study is, to our knowledge, the first to make use of data from large-scale repeated tournaments to assess the impact of monetary incentives on one-time and repeated winners. Assuming repeated winners are motivated by monetary incentives—whereas one-time winners may not be—allows us to disentangle the reactions of intrinsically motivated (one-time winners) vis-à-vis extrinsically-motivated users (repeated winners).

Literature Review

We review research on (1) monetary incentives and UGC, and (2) tournaments and relative performance evaluation on digital platforms.

Monetary Incentives and User-Generated Content

This study is related to a stream of research that has investigated how monetary incentives stimulate UGC (Table 1). Most prior work has either studied (1) piece-rate schemes that compensate contributors based on the number of posts (Burtch et al., 2018; Khern-am-nuai et al., 2018; Sun et al., 2017) or (2) performance-based "pay-per-view" schemes (or variants thereof) with a linear pay structure that compensate contributors based on views of their posts (Balbuzanov et al., 2019; Chen et al., 2019). Many of these studies have documented that monetary incentives often suffer from known drawbacks of extrinsic rewards, such as crowding out, potentially decreasing the quantity of UGC (Burtch et al., 2018; Sun et al., 2017; Wang et al., 2022). For example, publicly announced "token" awards can reduce UGC because they undermine users' intrinsic motivation (Sun et al., 2017). Balbuzanov et al. (2019) show that journalists reduce the number of contributions to online news articles under a pay-per-view vs. piece-rate contract and shift away from local news toward national-level news to reach a wider audience.

Despite growing interest in the effects of monetary incentives on UGC contributions, tournaments have received limited attention in prior research. The closest work to ours is Yu et al. (2022), who study a tournament-like incentive scheme on a restaurant review platform which awards a monetary incentive to the contributors who submitted the best review of the day. Considering only one-time winners, they find that contributors increase their reviews after receiving the reward. They argue that contributors feel recognized as experts by the platform, which, in turn, enhances their intrinsic motivation.

Unlike Yu et al. (2022), we examine both one-time and repeated winners of an *unexpected* reward awarded to winners using a more transparent selection process based on crowd voting. We shed light on contributors' competitive behaviors under such a relative performance incentive scheme. To our knowledge, this is the first study to systematically explore how relative performance incentive schemes affect contribution and evaluation behavior on digital platforms.

Tournaments and Relative Performance Evaluation

There is an extensive body of work on tournaments and relative performance evaluation in economics, dating back to the work of Lazear & Rosen (1981). This stream of research has shown that relative performance evaluation is beneficial in situations where inputs are not easily observed. Importantly, rewards in tournaments only depend on the relative performance and not on the "distance" between participants. Tournaments therefore eliminate shocks that are common to all participants (for example, changing production circumstances). This can make tournaments a suitable incentive scheme for fast-paced online environments, where the circumstances can change (for example, due to decreasing demand on a certain day) such that contributions could fail to generate substantial engagement because of insufficient investment or because demand was low. Consequently, if contributors are rewarded for being "best-in-class", they may be incentivized to post more—even on less busy days—because their payoff does not depend on the total number of views or votes. Thus, we expect that after learning of the tournament incentive scheme, they are, on average, more engaged, which should ensure a steady stream of UGC. We label this prediction the "engagement hypothesis".

Study	Context (Platform)	Country	Completion-contingent	Performance-contingent	
			Piece rate	**Linear pay structure**	**Tournament**
Wang et al. (2012)	Retailer (Amazon)	US	1 USD per review	0.25 USD per upvote	
Sun et al. (2017)	Shopping community	China	~0.25 USD per review		
Burtch et al. (2018)	Retailer	China	~1.50 USD per review		
Khern-am-nuai et al. (2018)	Retailer	China	~0.50 USD per review		
Balbuzanov et al. (2019)	News	Kenya	~1 USD per article	Pay-per-view with thresholds	
Kuang et al. (2019)	Q&A (Zhihu)	China		Set entry fee paid by each listener	
Chen et al. (2019)	Investment (Seeking Alpha)	US		10 USD per 1,000 views	
Wang et al. (2022)	Q&A (Zhihu)	China		Set entry fee paid by each listener	
Yu et al. (2022)	Restaurant	Asia			~10 USD for review of day

Table 1. Monetary Incentives on Digital Platforms

Yet, tournaments can also adversely affect contribution behavior. Participants have an incentive to take actions that diminish their competitors' chances to win the rewards—commonly known as sabotage (Harbring & Irlenbusch, 2011). In the context of digital platforms, participants can, for example, withhold upvotes, cast downvotes, or write negative comments. Riedl et al. (2024) observe sabotage in crowdsourcing contests. They show that high-ability contestants target the contributions of other high-ability contestants by assigning them low ratings when competing in the same contest. We extend and build upon these results by investigating whether dysfunctional behavior can also be induced by relative performance evaluation in the UGC context. Additionally, whereas Riedl et al. (2024) compare the ratings of contestants and non-contestants, we consider informed and uninformed contributors, which alleviates concerns of endogenous entry into tournaments. Thus, applied to our context, we expect that users become more competitive by trying to diminish the chances of other contributors to receive the highest voted contribution. We label this prediction the "sabotage hypothesis".

Research Setting

Incentive Scheme

We analyze the effect of unexpected monetary incentives on deal-sharing platforms in three European countries. The design and functionalities of the platforms are identical because they are part of a larger network of deal-sharing platforms. The incentive scheme was first launched on 22 September 2021 on one of the platforms (Country1), and subsequently introduced by the other two platforms on 01 October 2021 (Country2) and on 05 October 2021 (Country3), respectively. From October 2021 to May 2022, the platforms jointly rewarded more than 1,000 deals per month. The distribution of rewards across the three platforms is largely similar, with Country2 awarding slightly fewer deals (Figure 1a). Similarly, the number of users identified for our main analysis is comparable with 1,750 users in Country1, 1,736 users in Country2, and 1,332 users in Country3 (see section "Regression Results"). Over time, the share of contributors who are first-time winners decreases. Five months after the introduction, most winners are repeated winners (Figure 1b).

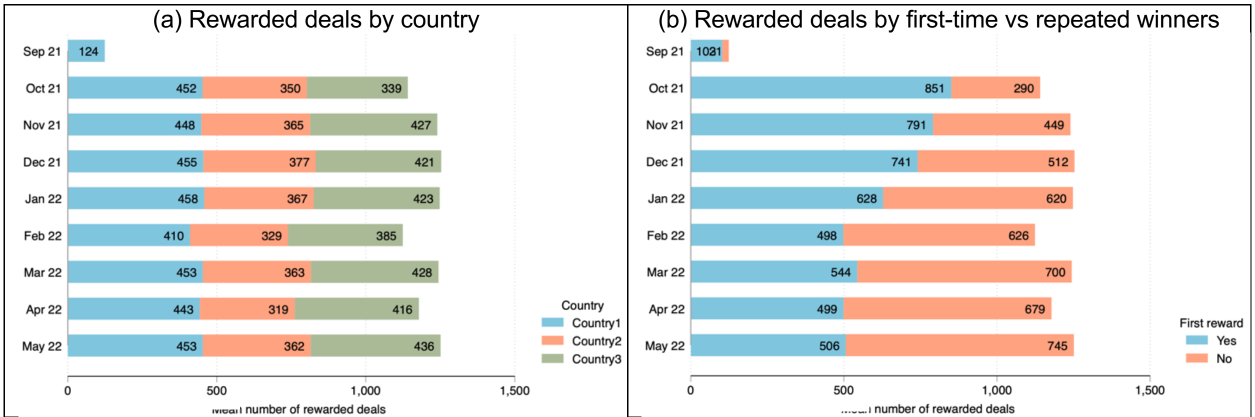

Figure 1. Reward Statistics

Identification Strategy

Our identification strategy hinges on the fact that only the most popular deal in a certain category is rewarded. We use a regression discontinuity design (RDD) by comparing the behavior of contributors who received the voucher by posting the most popular deal in a category with their runners-up who came in second (Figure 2). The identifying assumption of the RDD is that there is some randomness that determines the most popular deal on a given day. Contributors who receive the incentive are in the treatment group and contributors who post the runner-up deals in the same category on the same day are in the control group. Specifically, contributors are part of the control group only if they do not receive the incentive during our entire observation period (to avoid any potential spillover between treatments and controls). We identify 7,488 contributors, 5,079 in the treatment group and 2,409 in the control group ("full sample"). We also compile a balanced sample, where we include only the winners for which a control group contributor exists (2,409 in treatment and 2,409 in control). Finally, we construct a panel dataset at the contributor-week level so that each observation corresponds to a contributor and each period is one week.[2]

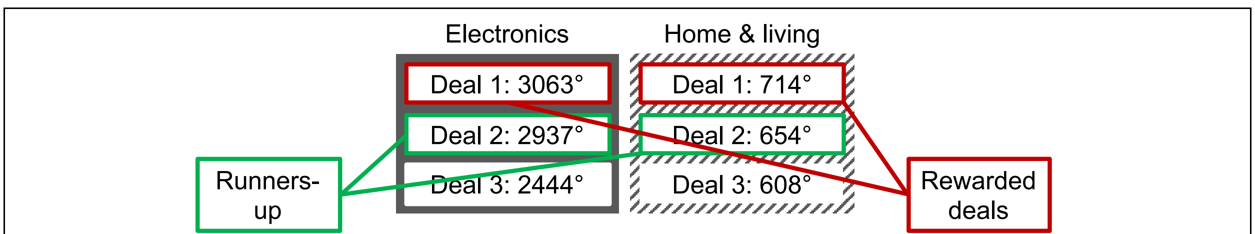

Figure 2. Identification Strategy

Measures

We use three dependent variables to measure contribution behavior. $NumDeals_{it}$ represents the number of deals posted by contributor i in week t, $NumUp_{it}$ represents the number of upvotes given by contributor i in week t, and $NumDown_{it}$ represents the number of downvotes given by contributor i in week t. $NumUp_{it}$ and $NumDown_{it}$ exclude votes given on users' own deals to measure interactions with other users instead of self-promotion (or demotion). We further track whether the deal was posted to the same category as the rewarded deal (or its runner-up), and whether up- or downvotes are given to deals in the same category. We log all three dependent variables to account for skewness. The correlation coefficients between the dependent variables during our main observation period were moderate: 0.32 for $NumDeals_{it}$ and $NumUp_{it}$, 0.34 for $NumDeals_{it}$ and $NumDown_{it}$, and 0.56 for $NumUp_{it}$ and $NumDown_{it}$). Notably, users remained engaged on the platform even when they did not post a deal. For example, in 56% of the weeks

[2] Despite the daily tournaments, we believe it is reasonable to aggregate data at a weekly level because of computational complexity and sparse data. In the four weeks prior to the first reward, contributors post 0.12 deals/week and give 1.14 up- and 0.54 downvotes/week. It also follows prior work, e.g., Yu et al. (2022) who study the effect of winning the best review of the day at the reviewer-week level.

where users did not post a deal ($NumDeals_{it}$ = 0), they still returned to the platform to upvote other deals. These results suggest that the dependent variables do not merely offer different ways to measure a user's visit to the platform, but rather meaningfully capture distinct activities.

Preliminary Analysis and Results

Model-Free Evidence

Figure 3 presents initial model-free evidence using the full sample. We normalize the dependent variables (log-transformed) for the treatment and control groups to four weeks prior to winning the first reward. In the left column, we show the contribution behavior across all categories. In the right column, we show the contribution behavior to the same category as the rewarded deal. Figures 3a and 3b show that treated users post more deals compared to the control group—across all categories and to the same category. Figures 3c and 3d show that treated users tend to give more upvotes to deals across all categories, but the pattern reverses for upvotes to deals in the same category. Figures 3e and 3f show that treated users tend to give more downvotes to deals across all categories, but the gap widens when considering downvotes to deals in the same category. These findings indicate that users seem to become more active after winning the reward. However, they might be strategically exploiting their knowledge about the tournament incentive scheme by withholding upvotes and giving more downvotes.

Regression Results

We formally conduct our analyses by using a difference-in-differences (DID) framework to evaluate the effect of receiving unexpected monetary rewards on recipients' subsequent behavior. We use the balanced sample, where each treated contributor corresponds to a control group, and select a study period of four weeks before to four weeks after users receive the first reward.

$$y_{it} = \beta_0 + \beta_1 Treat_i \times After_t + u_i + \tau_t + \varepsilon_{it}. \quad (1)$$

The variable y_{it} denotes contributor i's contribution behavior (i.e., number of deals, number upvotes, and number of downvotes) in week t. The coefficient β_1 of the DID estimator $Treat_i \times After_t$ captures the average treatment effect of receiving the unexpected monetary incentive on recipients' contribution behavior. We include contributor fixed effects u_i to account for time-invariant differences across contributors, and time fixed effects τ_t, including both calendar week dummies and the relative time distance between the observation week and the reward receiving week, to control for common shocks over time. Importantly, because each contributor is only active on one platform, our contributor fixed effects also control for time-invariant differences across platforms. Meanwhile, ε_{it} represents the error term. Finally, we cluster the standard errors at the contributor level. The results in Table 2 show that the effect of the unexpected incentive is positive and significant for all three dependent variables. Specifically, we find that receiving unexpected incentives leads to an average increase of 6.2% in number of deals posted by recipients in the first four weeks. Moreover, the number of up- and downvotes increase by 8.3% and 7.7%, respectively. The findings suggest that the winners posted more deals and voted more (both up and down). Thus, the unexpected incentive motivated them to engage with the community more after receiving the first reward, supporting the prediction of the engagement hypothesis.

DV	(1) $NumDeals_{it}$	(2) $NumUp_{it}$	(3) $NumDown_{it}$
$Treat_i \times After_t$	0.060***	0.080***	0.074***
	(0.010)	(0.019)	(0.016)
Observations	38,130	38,130	38,130
Users	4,818	4,818	4,818
Adj. R-squared	0.370	0.094	0.046
Note: OLS regressions are presented in cols. 1–3. All regressions include calendar week, relative week, and user fixed effects. Standard errors clustered by user are reported in parentheses. *** p < 0.01			

Table 2. Regression Results

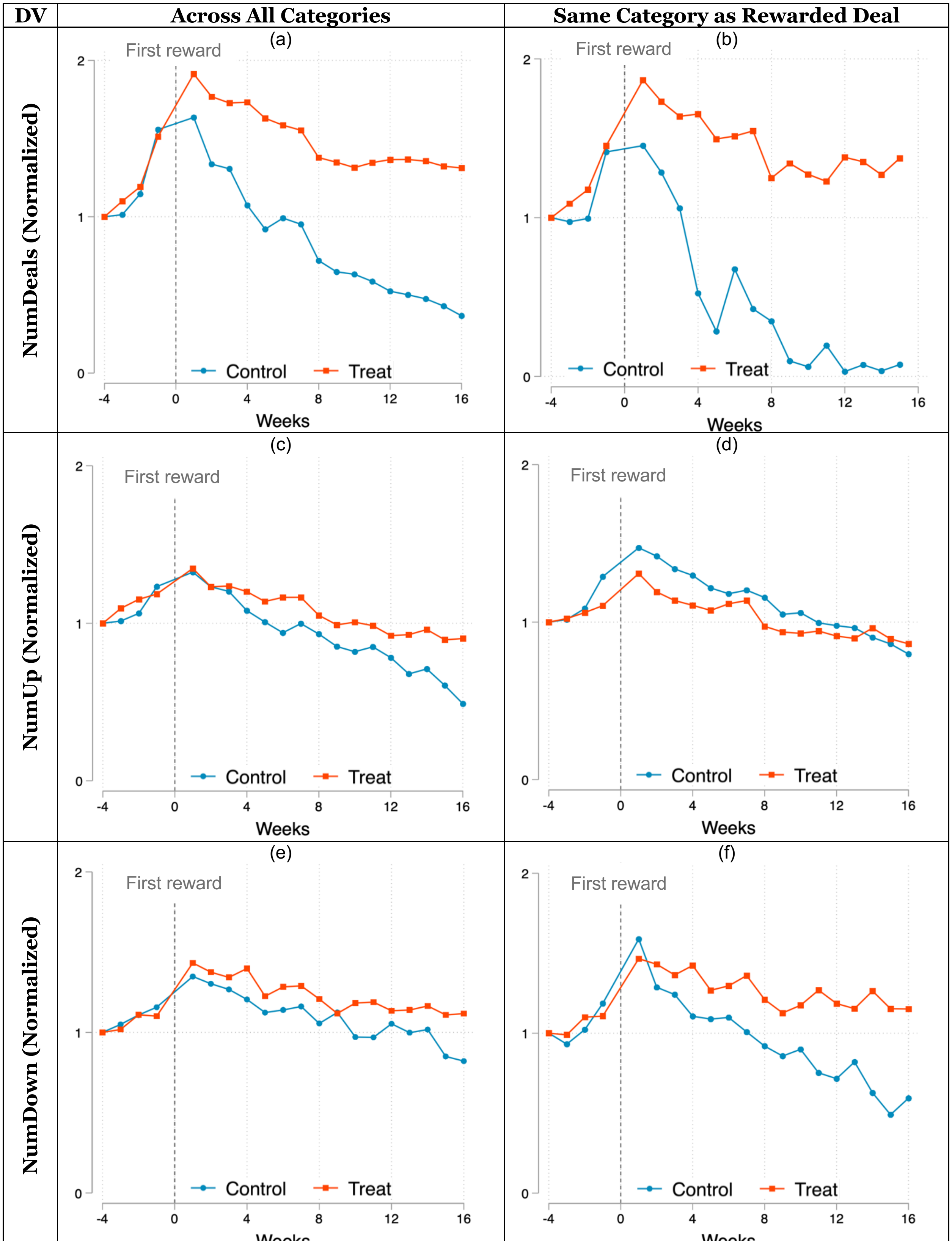

Figure 3. Model-Free Evidence

We now analyze the long-term effect from four weeks before to 16 weeks after receiving the first reward. We focus on treated users and their control groups who received the reward prior to 01 February 2022 to ensure that the post-treatment observation period is at least 16 weeks. In the spirit of Wang et al. (2022), we divide the post-treatment period into four periods of four weeks each, where $After1_t$ equals one in the first four-week period after the treatment, $After2_t$ equals one in the second four-week period, and so on. The results appear in Table 3 and suggest two key findings. First, the results in the first four weeks appear robust to restricting the sample to early winners, when the scheme was not widely known in the community. Second, in the long-run, winners continue to post more deals, they do not give more upvotes, and they continue to give more downvotes—but only in the same category as the first rewarded deal (cf. Figure 3). The results indicate that the reward effectively motivated users to increase their engagement by posting more deals. However, the incentive did not generate a sustained impact on other activities that were not directly incentivized, unless those activities contributed to earning the reward.

DV	$NumDeals_{it}$		$NumUp_{it}$		$NumDown_{it}$	
	(1) All categories	(2) Same category	(3) All categories	(4) Same category	(5) All categories	(6) Same category
$Treat_i \times After1_t$	0.072***	0.030***	0.060**	0.021	0.077***	0.026**
	(0.013)	(0.007)	(0.025)	(0.014)	(0.021)	(0.011)
$Treat_i \times After2_t$	0.068***	0.036***	0.027	0.008	0.059***	0.031***
	(0.013)	(0.007)	(0.026)	(0.014)	(0.021)	(0.011)
$Treat_i \times After3_t$	0.039***	0.018***	-0.002	0.005	0.028	0.019*
	(0.013)	(0.007)	(0.027)	(0.015)	(0.021)	(0.011)
$Treat_i \times After4_t$	0.032**	0.021***	-0.025	-0.003	0.019	0.021*
	(0.013)	(0.007)	(0.028)	(0.014)	(0.022)	(0.011)
Observations	63,560	63,560	63,560	63,560	63,560	63,560
Users	3,178	3,178	3,178	3,178	3,178	3,178
Adj. R-squared	0.221	0.397	0.120	0.044	0.056	0.022

Note: OLS regressions are presented in cols. 1–6. All regressions include calendar week, relative week, and user fixed effects. Standard errors clustered by user are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 3. Long-Term Effect

Implications and Next Steps

Platforms use various monetary reward strategies to incentivize UGC (Table 1). Earlier studies documented a crowding out effect of completion-contingent incentive schemes, but more recent research demonstrates the merits of performance-contingent schemes in enhancing the quantity and quality of UGC (e.g., Yu et al., 2022). Our results support the engagement hypothesis because informed users become more engaged—especially in incentive relevant categories. However, we highlight a novel effect of performance-contingent incentive schemes in the field: if only the highest voted content receives recognition, users potentially withhold their upvotes and engage in sabotage behavior after learning about the incentive scheme (Dorner et al., 2020). Our findings are consistent with the sabotage hypothesis, suggesting that tournaments and relative performance evaluation can lead to competitive aggressiveness (Feichter et al., 2022). This has important implications for platform managers because tournament incentive schemes can increase contributions but unintentionally induce competition among contributors. Thus, tournaments could inadvertently demotivate and drive some contributors out of the community. They could also distort content ratings on the platform, especially as they become widely known. Future research should study how the negative effects of tournaments could be mitigated, for example, by nudging users to vote honestly.

We now highlight three important ways of extending our preliminary analysis. First, we plan to enhance the identification strategy by employing an alternative RDD for which we select deals within a certain range of votes of the winning deal as a control group. By strictly using the first runner-up, we currently disregard that the runner-up could be trailing the winner by a large margin (which would affect the randomness of their order). Nonetheless, Figure 3 suggests that treatment and control groups largely follow a similar trend in absence of the treatment, suggesting a causal interpretation of the results. Second, we plan to analyze the heterogeneous effects on one-time vs. repeated winners to understand how different types of users (i.e., users with intrinsic vs. extrinsic motivation) react to the rewards. Further, we plan to establish the heterogeneity of effects that emerge according to users' characteristics (e.g., tenure). We believe that these results have important managerial implications because it could inform platforms regarding who should be informed early on of a tournament incentive scheme. Third, we plan to further analyze the competitive behaviors of informed users by using alternative dependent variables (e.g., effort, quality) and a daily panel.

Using alternative dependent variables could help to understand whether contributors try to enhance the chances of winning the reward beyond strategic voting. Using a daily panel could provide further insights into the voting behavior of contributors on the same days as they submit their own deals, enhancing our confidence that their behavior is indeed strategic.

Acknowledgements

We thank our partner company for providing the data and invaluable support that made this research possible. The work described in this paper was supported by a grant from the Germany/Hong Kong Joint Research Scheme sponsored by the Research Grants Council of Hong Kong and the German Academic Exchange Service [G-HKUST602/22]. Florian Pethig received support from the Joachim Herz Foundation.

References

Balbuzanov, I., Gars, J., & Tjernström, E. (2019). Media and motivation: the effect of performance pay on writers and content. *Working Paper*.

Burtch, G., Hong, Y., Bapna, R., & Griskevicius, V. (2018). Stimulating online reviews by combining financial incentives and social norms. *Management Science*, *64*(5), 2065–2082.

Casas-Arce, P., & Martinez-Jerez, F. A. (2009). Relative performance compensation, contests, and dynamic incentives. *Management Science*, *55*(8), 1306–1320.

Chen, H., Hu, Y. J., & Huang, S. (2019). Monetary incentive and stock opinions on social media. *Journal of Management Information Systems*, *36*(2), 391–417.

Deodhar, S. J., & Gupta, S. (2023). The impact of social reputation features in innovation tournaments: Evidence from a natural experiment. *Information Systems Research*, *34*(1), 178–193.

Dorner, V., Giamattei, M., & Greiff, M. (2020). The market for reviews: Strategic behavior of online product reviewers with monetary incentives. *Schmalenbach Business Review*, *72*, 397–435.

Eckles, D., Karrer, B., & Ugander, J. (2017). Design and analysis of experiments in networks: Reducing bias from interference. *Journal of Causal Inference*, *5*(1), 20150021.

Feichter, C., Moers, F., & Timmermans, O. (2022). Relative performance evaluation and competitive aggressiveness. *Journal of Accounting Research*, *60*(5), 1859–1913.

Harbring, C., & Irlenbusch, B. (2011). Sabotage in tournaments: Evidence from a laboratory experiment. *Management Science*, *57*(4), 611–627.

Huang, Y., Singh, P. V., & Ghose, A. (2015). A structural model of employee behavioral dynamics in enterprise social media. *Management Science*, *61*(12), 2825–2844.

Khern-am-nuai, W., Kannan, K., & Ghasemkhani, H. (2018). Extrinsic versus intrinsic rewards for contributing reviews in an online platform. *Information Systems Research*, *29*(4), 871–892.

Kuang, L., Huang, N., Hong, Y., & Yan, Z. (2019). Spillover effects of financial incentives on non-incentivized user engagement: Evidence from an online knowledge exchange platform. *Journal of Management Information Systems*, *36*(1), 289–320.

Lazear, E. P., & Rosen, S. (1981). Rank-order tournaments as optimum labor contracts. *Journal of Political Economy*, *89*(5), 841–864.

Liu, Y., & Feng, J. (2021). Does money talk? The impact of monetary incentives on user-generated content contributions. *Information Systems Research*, *32*(2), 394–409.

Riedl, C., Grad, T., & Lettl, C. (2024). Competition and collaboration in crowdsourcing communities: What happens when peers evaluate each other? *Organization Science*, forthcoming.

Roth, J., Sant'Anna, P. H. C., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*, *235*(2), 2218–2244.

Shen, W., Hu, Y. (Jeffrey), & Ulmer, J. R. (2015). Competing for attention: An empirical study of online reviewers' strategic behavior. *MIS Quarterly*, *39*(3), 683–696.

Sun, Y., Dong, X., & McIntyre, S. (2017). Motivation of user-generated content: Social connectedness moderates the effects of monetary rewards. *Marketing Science*, *36*(3), 329–337.

Wang, J., Ghose, A., & Ipeirotis, P. (2012). Bonus, disclosure, and choice: What motivates the creation of high-quality paid reviews? *Proceedings of the 33rd International Conference on Information Systems*, 1-15.

Wang, J., Li, G., & Hui, K.-L. (2022). Monetary incentives and knowledge spillover: Evidence from a natural experiment. *Management Science*, *68*(5), 3549–3572.

Yu, Y., Khern-am-nuai, W., & Pinsonneault, A. (2022). When paying for reviews pays off: The case of performance-contingent monetary rewards. *MIS Quarterly*, 46(1), 609–626.