Eyes on the Prize: Increasing the Prize May Not Benefit the Contest Organizer in Multiple Online Contests

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Short Paper

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Abstract

Given the proliferation of online platforms for crowdsourcing contests, we address the inconsistencies in the extant literature about the behavioral effects of increasing the prize awarded by contest organizers. We endeavor to resolve these inconsistencies by analyzing user behavior in a highly controlled experimental setting in which users can participate (by exerting real effort rather than stated effort) in multiple online contests that vary only in their prizes. The analysis of the behavior of 731 active participants in our first experiment showed that both participation and effort were non-monotonic with the prize, that the low-prize contest was the most effective for the organizers, and that increasing the prize of the low-prize or high-prize contest by 50% actually decreased the benefits for organizers. Our findings advance theory by providing insight into when and why extrinsic incentives fail to produce the desired effects in crowdsourcing contests.

Keywords: Crowdsourcing, contests, prize, user behavior, online experiment

Introduction

In the last two decades, online platforms for crowdsourcing contests, such as 99design, Topcoder, and Kaggle, have emerged as a way for firms to address the crowd and perform various tasks (e.g., logo design, content creation, coding), allowing firms to source labor better, faster, and more efficiently than before (Chen et al., 2014). On these platforms, tasks are presented to the crowd as contests: a requester (i.e., the contest organizer) posts a task and offers a monetary reward for the winning solution. Contestants (i.e., platform users) submit solutions to the contests they choose to enter, and the requester chooses the best solution and awards the prize. Users on such platforms usually have limited effort resources (in particular, time), which allow them to participate only in a limited number of contests. They most likely choose to enter the contests in which they have higher chances of winning the prize according to their estimation (Ge et al., 2010), which depends on their expectations about their performance relative to the other contestants (Mo et al., 2018). For the contest organizers, having more contestants is critical to ensure they receive qualitatively acceptable solutions, since a larger pool of participants provides a more diverse set of ideas and potentially higher quality solutions (Chen et al., 2014). Crowdsourcing contest platforms can be characterized as an environment of competition among multiple contests, where every contest organizer competes for the attention of potential contestants (Segev, 2020).

Given that users exert effort in crowdsourcing contests primarily to win the prize offered by contest organizers, the prize has emerged as a key contextual determinant of user behavior in research on contests.

The common finding in this literature is that increasing the prize leads to higher contest entry, higher effort, and better-quality solutions (Dechenaux et al., 2015; Morgan et al., 2012). The empirical literature on crowdsourcing contests has repeatedly demonstrated that a higher prize leads to higher participation (Araujo, 2013; Cappa et al., 2019; Chen et al., 2014; Dargahi et al., 2021; Li and Hu, 2017; Liu et al., 2014; Shao et al., 2012; Yang et al., 2009) and better-quality solutions (Liu et al., 2014; Kireyev, 2015). However, recent empirical studies have also shown that increasing the prize unnecessarily increases participation and effort (Bockstedt et al., 2015; Deodhar, 2020; Jeppesen and Lakhani, 2010; Liu et al., 2021; Stol et al., 2019), particularly when higher prizes are associated with higher task complexity and greater resource demand (Jain and Deodhar, 2022; Sun et al., 2012). Given these contradicting findings, we have little understanding of *whether increasing the prize in crowdsourcing contests indeed benefits the organizers by increasing user participation and effort*, which serves as the research question motivating our work in progress.

Our ability to integrate previous contest research to answer this research question is primarily limited by the inclination of previous studies to adopt one of two dominant approaches—studies either employed observational methods to analyze field data collected by crowdsourcing platforms (e.g., Araujo, 2013; Liu et al., 2021) or used experimental methods to analyze how variance in the characteristics of a single contest affects user behavior (e.g., Finnerty et al., 2013; Liu et al., 2014). Observational studies are advantageous because of their ability to record user behavior in realistic settings, where users can choose among multiple contests, but this advantage comes at the cost of challenges to attribute causality to the effects of the focal variable. While these challenges can be addressed by taking an experimental approach and controlling for extraneous variance, experimental studies on contests have generally analyzed user behavior in settings of a single contest, largely overlooking the potential effects of having alternative contests in which users can participate, resulting in evidence of positive prize effects.

To answer the above research question, we designed a platform for conducting controlled online experiments that simulates a multiple contest environment. In the first experiment conducted as part of this study, each participant could spend up to two hours in three contests, which varied in their monetary prizes but were identical in all other aspects. We manipulated the ratios among the prizes in the three contests and observed the participants' behavior in each contest (participation and effort) and the effectiveness of each contest for the contest organizer (total effort and quality of the best solution relative to the prize awarded). The findings suggest that user expectations that other users will choose to compete in a contest with a higher prize may cause them to compete in a contest with a lower prize, resulting in higher effectiveness of the lower prize for the organizer. Our compelling findings, in a realistic yet highly-controlled environment, open a new avenue for analyzing user behavior in multiple online contests.

Literature Review

Despite the rapid growth in research on crowdsourcing contests, most previous research on contests analyzes a contest as an isolated event. The common finding in the contest literature is that increasing the monetary prize results in higher contest entry, higher effort, and better-quality solutions (Dechenaux et al., 2015; Morgan et al., 2012). The literature examines three main behavioral outcomes related to contestants: (1) participation (decision of whether to enter a focal contest), (2) effort (the level of effort exerted), and (3) performance (the quality of a solution) (Jain and Deodhar, 2022). Performance is commonly assumed to be dependent on the contestant's ability and effort (Segev, 2020).

Several theoretical papers have used different contest models to describe a situation of competing contests (Azmat and Möller, 2009; Ge et al., 2010; Lavi and Shiran-Shvarzbard, 2020; Stouras et al., 2020). A theoretical model that captures such an environment is largely intractable and many relaxing assumptions must be taken to yield analytical results.

Empirical research on crowdsourcing contests is growing rapidly due to the easy access to large data sets from websites that hold such contests. The main goal of such research is to identify and categorize the incentives that affect contestants' behavior, aiming to design better crowdsourcing contest platforms. It is generally assumed that a higher monetary prize in a crowdsourcing contest can lead to desirable contestant behaviors (Hossain, 2018). The empirical literature on crowdsourcing contests does provide considerable evidence that a higher prize leads to higher participation (Araujo, 2013; Cappa et al., 2019; Chen et al., 2014; Dargahi et al., 2021; Li and Hu, 2017; Liu et al., 2014; Shao et al., 2012; Yang et al., 2009) and better-quality solutions (Liu et al., 2014; Kireyev, 2015). However, the literature is inconsistent about these effects. According to Stol et al. (2019), higher prizes do not significantly increase participation. Other empirical studies show a negative association between prize size and both participation (Deodhar, 2020; Jeppesen and Lakhani, 2010) and effort (Bockstedt et al., 2015). Liu et al. (2021) show that moderate prizes maximize participation. Research suggests that a higher prize might signal a more complex task that potentially requires more resources from contestants (Jain and Deodhar, 2022). For instance, Sun et al. (2012) showed that task complexity moderates the positive effect of extrinsic incentives on participation. Therefore, a higher prize may discourage certain contestants from participating based on their previous experience (Mo et al., 2018). Walter and Back (2011) suggest that a higher prize may increase the number of submissions, but often of lower quality, and Huang et al. (2012) show that increasing the prize may decrease submission quality.

Importantly, all empirical studies reviewed above implemented observational methods, analyzing data collected from real platforms. A few studies conducted surveys of users of crowdsourcing contest platforms (e.g., Dargahi et al., 2021; Jeppesen and Lakhani, 2010; Lee et al., 2015). To the best of our knowledge, there have been no controlled experiments in which participants exert actual effort (rather than allocate "effort capacity") in multiple concurrent contests.

Theory and Hypothesis

To provide a theoretical foundation for our empirical investigation, we construct a game theoretic model, generalizing the model of Stouras et al. (2022) of a single contest to a model that encompasses both contest organizers and contestants, thereby capturing the entire environment of multiple simultaneous contests. In the model, we have a set M of contest organizers on the platform. An organizer determines the prize of her contest that will be awarded to the winner. There is also a set N of potential contestants. A contestant is characterized by a (possibly contest specific) ability, which affects the quality of her solution. A contestant's abilities are her own private information. It is common knowledge that contestants' abilities are drawn i.i.d from a known distribution. We assume that if a contestant participates in a contest by exerting effort, then the quality of her solution is a function of her ability, her effort, and some random effect. The winner of a contest is the contestant with the highest solution quality in this contest. Furthermore, a contestant's cost of exerting effort is equal to her effort, and we assume that each contestant is endowed with a "budget" such that her total cost of effort cannot exceed the budget. The organizers only enjoy the winning solution, i.e., they choose the prize in order to maximize the expected quality of the highest quality solution.

We analyze the special case in which there are two organizers and two contestants, there is no randomness, contestants are ex-ante symmetric in their budget, the ability of each contestant is the same across contests and is drawn independently from a uniform distribution on [0,1], and the contestants arrive sequentially (the second contestant observes the qualities of the first contestant solutions). Then we can calculate the sum of contestants' efforts in both contests and show that there is a range of parameters for which the sum of efforts of the contestants in Contest 1 increases/decreases when we increase the prize of Contest 2.

Our working hypothesis is based on the reasoning that the prize can attract contestants by creating powerful extrinsic motivation, yet deter them by signaling a higher competition that requires higher effort with lower winning chances. In particular, increasing the prize in a specific contest may cause contestants to assume that the contest will become more attractive for others, thereby causing them to choose to participate in other contests to increase their chances of winning, leading to the following working hypothesis:

Hypothesis: *Increasing the prize of a contest in a multiple contest situation may lead to lower user participation and effort in that contest.*

Methodology

By using controlled experiments, we gained two major advantages. First, we exogenously manipulated the monetary prizes offered in the contests and examined their causal effects on participants' behavior, while allowing no variance in contextual variables (e.g., task complexity) that could serve as alternative explanations for the observed effects. Second, the control over the empirical setup enabled us to measure the effort directly and objectively, while effort is usually a behavioral variable that can be observed only indirectly (e.g., proxied by performance) or subjectively (e.g., by experts' evaluations of solutions) (Charness et al., 2018).

Experimental design. Each participant was randomly assigned to one of four parallel multiple contest environments, denoted as "contest sets"—Baseline [$10, $30, $60], Low+ [$15, $30, $60], Medium+ [$10, $45, $60], and High+ [$10, $30, $90]. The contest prize (low, medium, or high) was essentially a within-subjects independent variable, whereas the contest set was a between-subjects independent variable, allowing us to control the effects of increasing any of the three prizes in the Baseline set by 50%. Each participant could participate in none, one, or any combination of the contests in the available contest set. Two key dependent variables were measured for each participant in each contest: participation and effort. Potential extraneous variables were addressed either by fixing all contextual variables other than the contest prize or by randomly assigning participants to experimental conditions.

Procedure. The experiment was conducted on a website that was developed specifically for this study, simulating a multiple contest situation. The following instructions were presented to participants: they are offered to participate in three contests, identical in every aspect other than the monetary prize the winner receives; performance is measured separately for each contest, so they can win the prize of each contest in which they participate; the contests remain open for them for two hours, during which they can freely enter and exit any contest, including the website itself. Participants were informed that they compete in the contests against other participants of the experiment. Next, participants were asked to answer several demographic questions (age, gender, years of education, country of residence, and employment status) as part of registration for the experiment, for which they received $0.5 irrespective of their participation in the contests. Participants who completed the registration could participate in the contests. Each contest presented matrices that were generated automatically in the same way for all contests in the experiment. Each matrix was four-by-three and contained 12 decimal numbers between 0 and 10 with two digits after the decimal point. The matrix is solved by finding the only two numbers that sum up exactly to 10 (e.g., 3.56 and 6.44),[1] under a time limit of 30 seconds. Solving a matrix in a contest successfully within the allotted time gave the participant 1 point in that contest. In each contest, participants could solve as many matrices as they want to earn more points. For each matrix solution, an indication of correctness and the correct solution were presented before the next matrix appeared in order to promote participant motivation and trust. The participant who earned the most points in each contest won the prize of that contest. Before starting the contests, participants had to solve an example matrix to ensure they understood the task. After completing the example, participants were presented with the three contests according to the contest set randomly assigned to them. They could enter contests via a menu page that clearly presented the three contests and their prizes. The performance of a participant in a contest was accumulated over the two hours, after which access to the website expired. Participants were informed of their access expiration time on the menu screen. After access to the website of all participants expired, the prize of each contest in each set (participants did not compete across sets to maintain the integrity of our instructions that all of them compete for the same prizes) was added to the payment of the winning participant (a total of $450 was awarded to participants as prizes).

Participants. In total, 949 Amazon Mechanical Turk workers, recruited via CloudResearch, completed the registration phase and received a $0.5 payment regardless of their performance in the contests.

Measures. A participant was considered to be "active" in a contest if she submitted (i.e., solved correctly or incorrectly) at least three matrices in that contest (to ensure that participation was not based on one or two trials). The *participation* of a participant in a contest was '1' if she was active in that contest, and '0' otherwise. The *effort* exerted by a participant in a contest she was active in was measured as the number of matrices submitted by her in that contest (the effort exerted by a participant in a contest she was not active in was determined to be zero). The *performance* of a participant in a contest was measured as the number of matrices correctly solved by her in that contest (i.e., points she earned in that contest). Consistent with previous experimental studies on contest entry (e.g., Cason et al., 2010), the *ability* of a participant was measured by the following formula (considering all three contests):

$$\frac{points\ earned\ in\ the\ first\ 10\ matrix\ submissions}{min(10,\ total\ matrix\ submissions)}$$

[1] The matrix task was introduced by Mazar et al. (2008) and has been used since then in more than 100 experiments.

For example, the ability of a participant who submitted more than 10 matrices, and earned 7 points in the first 10 matrix submissions, was 0.7. The ability of a participant who submitted 5 matrices and earned 4 points was 0.8. By evaluating the ability only based on the first 10 matrix submissions of participants, we eliminate the learning effect that may arise as participants solve more matrices, thus mitigating the possibility of reverse causality between effort and ability.

Results

Of the 949 participants who completed the registration phase, 731 were active in at least one contest. These active participants were similar in gender and employment status to those who were not active (active participants were significantly older with significantly more years of education). Active participants, mostly from the US, had a mean age of 41.4 (STD 12.9) years, a mean of 15.5 (STD 2.9) years of education, and 47.5% of them were female. On average, each participant spent 38.1 (STD 41.3) minutes on the website and submitted 67.1 (STD 92) matrices in all three contests, of which 46.6 (STD 75.5) matrices were solved correctly. On average, matrices were solved correctly in 14.7 (STD 7.5) seconds and incorrectly in 25.3 (STD 8.5) seconds. The ability variable had a mean of 0.6 (STD 0.25). Of the three contests, 67% of participants exerted effort only in one contest, 19.7% divided their effort between two contests, and 13.3% divided their effort among all three contests. The behavior of participants at the contest level is summarized in Table 1.

Contest Set	Contest	Prize	Active participants	Mean active effort	Total effort	Total effort per $	Winner	Winner per $
Baseline	Low	$10	107	35.4	3784	378.4	157	15.7
	Medium	$30	54	31.3	1689	56.3	121	4.0
	High	$60	108	74.6	8052	134.2	507	8.5
Low+	Low	$15	119	27.4	3257	217.1	198	13.2
	Medium	$30	56	37.2	2082	69.4	291	9.7
	High	$60	85	63	5357	89.3	271	4.5
Medium+	Low	$10	105	31.2	3278	327.8	181	18.1
	Medium	$45	63	53.9	3396	75.5	384	8.5
	High	$60	108	57.9	6254	104.2	426	7.1
High+	Low	$10	111	32.8	3637	363.7	259	25.9
	Medium	$30	48	33.3	1597	53.2	377	12.6
	High	$90	105	62.4	6555	72.8	601	6.7

Notes. The 731 active participants were assigned to Baseline (184 participants), Low+ (183 participants), Medium+ (183 participants), and High+ (181 participants) contest sets. *Active participants* is the number of participants who submitted at least three matrices in a contest. *Mean active effort* is the mean effort exerted in a contest by participants that were active in that contest (without zero values for nonactive participants). *Total effort* is the total number of matrices submitted in a contest by all active participants. *Total effort per $* is the total number of matrix submissions the organizer "bought" with $1, calculated by dividing the total effort in a contest by its prize. *Winner* is the number of matrices solved correctly by the winner in a contest (the highest score achieved by a participant). *Winner per $* is the number of matrices solved correctly by the best performing participant "bought" with $1 by the organizer, calculated by dividing the performance of the winner in a contest by it prize.

Table 1. Participants' behavior in the experiment

Effects on Participation and Effort

To statistically test the effects of the prizes on participants' behavior, we estimated two regression models. In both models, the unit of analysis was a participant in a contest, i.e., the data set included three records for each participant, one for each contest (participation and effort were 0 if the participant was not active in the contest). Thus, the data set for these analyses included 2193 records for the 731 active participants.

Both models included fixed effects for the contest prize (low, medium, or high), contest set (Baseline, Low+, Medium+, or High+), and the interaction between them. The models also included effects for the following control demographic variables: age, gender, years of education, and employment status. Finally, the models included effects for the ability measure and for its interaction with the contest prize. The ability was centered with respect to its mean to reduce the multicollinearity threat that might arise when the estimated models include multiple terms with the same continuous variable (Jaccard and Turrisi, 2003). The results of the regression models are presented in Table 2 (these results were robust to the inclusion of participant fixed effects).

	Model 1 – Participation			**Model 2 – Effort**		
Effect	**Coeff**	**Std. Error**	**Sig.**	**Coeff**	**Std. Error**	**Sig.**
(Intercept)	0.787	0.4810	0.102	2.478	0.5569	<.001
Prize – medium	**-1.229**	**0.2230**	**<.001**	**-0.820**	**0.2625**	**0.002**
Prize – high	0.016	0.2141	0.941	**0.609**	**0.2591**	**0.019**
Set – Low+	0.329	0.2186	0.133	-0.182	0.2591	0.483
Set – Medium+	-0.035	0.2146	0.870	-0.119	0.2603	0.647
Set – High+	0.176	0.2166	0.416	0.077	0.2658	0.773
Age	-0.005	0.0041	0.219	0.000	0.0048	0.976
Gender – other	-0.717	0.6472	0.268	**-1.540**	**0.7374**	**0.037**
Gender – female	**0.276**	**0.0939**	**0.003**	0.049	0.1115	0.658
Years of education	0.007	0.0162	0.675	0.036	0.0197	0.070
Ability	-0.297	0.3067	0.333	0.385	0.3981	0.333
Medium prize × Low+ set	-0.228	0.3172	0.472	0.359	0.3666	0.327
Medium prize × Medium+ set	0.283	0.3120	0.364	**0.783**	**0.3696**	**0.034**
Medium prize × High+ set	-0.270	0.3201	0.398	-0.178	0.3737	0.635
High prize × Low+ set	**-0.788**	**0.3048**	**0.010**	0.026	0.3677	0.944
High prize × Medium+ set	0.058	0.3030	0.848	-0.011	0.3639	0.975
High prize × High+ set	-0.157	0.3047	0.605	-0.207	0.3689	0.575
Ability × Medium prize	0.574	0.4456	0.198	0.236	0.5603	0.673
Ability × High prize	0.596	0.4266	0.163	**1.277**	**0.5267**	**0.015**

Notes. N=2193. The explained variable of Model 1 was the participation of a participant in the contest ('1' – yes, '0' – no); The data set included 1069 (49%) records of '1' and 1124 (51%) records of '0'. The explained variable of Model 2 was the effort exerted by a participant in the contest (including values of '0' for nonactive participants). Models 1 and 2 also included effects for employment status categories, which were all statistically nonsignificant. Baseline conditions were 'low' for the prize variable and 'baseline' for the set variable.

Table 2. Results of regression models for participation and effort

Participation. To examine the effects on the participation in each contest, we estimated a logistic regression model, predicting the participation of a participant in a contest. The regression results indicate that the medium-prize contest significantly attracted the fewest participants among the three contests (p<0.001). The high-prize contest attracted significantly less participants when the prize of the low-prize contest was increased by 50% (p=0.01). Overall, females participated significantly more than males (p=0.003). Neither the rest of the demographic controls nor the ability measure significantly affected participation. A possible explanation for the lack of a significant effect of ability on participation is the fact that participants could not evaluate their ability in the matrix task before making entry decisions.

Effort. To examine the effects on the effort exerted in each contest, we estimated a negative binomial regression model, predicting the effort exerted by a participant in a contest. The prediction for each contest was among all study participants, including those who chose not to participate in that contest, based on the reasoning that organizers want to maximize effort among all platform users exposed to their contest. Since the dependent variable was a count measure with overdispersion, we fitted a negative binomial model instead of a Poisson model, because it has an extra parameter that captures the overdispersion of data. The regression results show that participants exerted significantly the most effort in the high-prize contest (p=0.019), and the least effort in the medium-prize contest (p=0.002). The participants exerted significantly more effort in the medium-prize contest when its prize was increased by 50% (p=0.034). The demographic controls did not significantly affect the effort (except for gender 'other', which was only 0.5% of the data set). Interestingly, ability had a positive effect on effort only in the high-prize contest (p=0.015): higher-ability participants exerted significantly more effort than lower-ability participants in the high-prize contest, whereas participants with different levels of ability exerted similar levels of effort in the medium-prize and low-prize contests. This finding suggests that higher prizes may have favorable effects for higher-ability participants.

Benefits to Contest Organizers

The effectiveness of a contest can be measured by the *total effort* exerted in it relative to the prize awarded. As can be seen in Table 1, the low-prize contest received the highest value of total effort per $, irrespective of the contest set. Therefore, the low-prize contest was the most effective for the organizers because they “bought” the most matrix submissions per $1 invested. Additionally, according to this index, the least effective contest was the medium-prize contest. However, the contest organizer may aim at maximizing the *quality of the best solution* rather than the total effort. As can be seen in Table 1, the low-prize contest received the highest value of winner per $, irrespective of the contest set, implying that the organizers of the low-prize contests “bought” the highest quality solutions relative to their investment.

The random assignment of participants into four contest sets allowed us to examine the effects of increasing any of the three prizes in the Baseline set by 50% on the values presented in Table 1. A comparison of sets Baseline and Low+ (which are similar in their medium-prize and high-prize contests and different in their low-prize contests) shows that increasing the prize of the low-prize contest by 50% actually decreased mean active effort, total effort, total effort per $, and winner per $ in this contest (only the best performance increased). Likewise, a comparison of sets Baseline and High+ (which are similar in their low-prize and medium-prize contests and different in their high-prize contests) shows that increasing the prize of the high-prize contest by 50% actually decreased mean active effort, total effort, total effort per $, and winner per $ in this contest (again, only the best performance increased).

Discussion and Future Experiments

This study aims to advance the understanding of how the prize affects the outcomes of a contest when participants choose among multiple online crowdsourcing contests. Our first experiment showed that the least attractive contest, in terms of participation and effort exerted by a participant, was the medium-prize contest, implying that both participation and effort were non-monotonic with the prize. Second, while the total effort and best performance were generally the greatest in the high-prize contest (excluding the winner in set Low+), the low-prize contest was the most effective for the organizers in terms of total effort and quality of the best solution relative to the prize awarded. Furthermore, we found that *increasing* the prize of the low-prize contest or the high-prize contest by 50% actually *decreased* effort, total effort, total effort per $, and winner per $ in these contests. These findings provide support for our working hypothesis, confirming that increasing the prize of a contest in a multiple contest situation may lead to lower participation and effort in that contest.

This work is currently in progress. We plan to continue this work in two additional online experiments, which will be based on the research setting and platform used in the experiment reported here. These additional experiments will serve two purposes. First, they will allow us to demonstrate the robustness of the findings reported here that increasing the prize in online crowdsourcing contests unnecessarily leads to better outcomes when multiple contests are available to participants. Second, they will allow us to examine how behavioral outcomes are affected by the number of contests and the variance of prizes, as these potentially important variables were relatively fixed in our first experiment. These additional experiments will allow us to address the main limitations of our first experiment, namely, the construction of settings with a relatively small number of homogenous contests. However, the ability to generalize our findings to different settings of crowdsourcing contests will remain limited by our specific experimental setting, which engages individuals (vs. teams) in a closed-ended (vs. open-ended) task with a winner-takes-all (vs. multi-tier) prize. Future research would have to address the full gamut of existing crowdsourcing contests.

This study has important theoretical and practical implications. From a theoretical standpoint, an analysis of the causal effects of increasing the prize in a single contest on user behavior when users can participate in multiple contests represents an important stage in the evolution of research on crowdsourcing contests. Our findings advance theory by providing insight into when extrinsic incentives may fail to have the desired effects in crowdsourcing contests. Because previous work on crowdsourcing contests has primarily either used observational methods or experimentally studied a single contest, this study contributes to the literature by uncovering the causal relationship between reward and behavioral outcomes while ruling out alternative explanations that arise in observational studies. From a practical standpoint, the knowledge gained in this study is important for a better design of crowdsourcing contest platforms to enhance the welfare of all parties involved.

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