

# Understanding Over Participation in Simple Contests

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## Abstract

One key motivation for using contests in real-life is the substantial evidence reported in empirical contest-design literature for people’s tendency to act more competitively in contests than predicted by the Nash Equilibrium. This phenomenon has been traditionally explained by people’s eagerness to win and maximize their relative (rather than absolute) payoffs. In this paper we make use of “simple contests”, where contestants only need to strategize on whether to participate in the contest or not, as an infrastructure for studying whether indeed more effort is exerted in contests due to competitiveness, or perhaps this can be attributed to other factors that hold also in non-competitive settings. The experimental methodology we use compares contestants’ participation decisions in eight contest settings differing in the nature of the contest used, the number of contestants used and the theoretical participation predictions to those obtained (whenever applicable) by subjects facing equivalent non-competitive decision situations in the form of a lottery. We show that indeed people tend to over-participate in contests compared to the theoretical predictions, yet the same phenomenon holds (to a similar extent) also in the equivalent non-competitive settings. Meaning that many of the contests used nowadays as a means for inducing extra human effort, that are often complex to organize and manage, can be replaced by a simpler non-competitive mechanism that uses probabilistic prizes.

## Introduction

Contests are an important and widely in use mechanism for eliciting individual efforts (Araujo 2013; Vojnovic 2016). In fact, many economic, political and social environments can be described as contests where contestants expend some resources in order to win one or more prizes. Perhaps the most famous crowdsourcing contest is the Netflix Prize Challenge which was an open competition over improving the accuracy of user’s movie preference predictions used by Netflix ([www.netflixprize.com](http://www.netflixprize.com)), with a one million USD prize. Other examples include the DARPA challenges (Robotics Challenge, Grand Challenge), which are high-payoff contests for developing technologies to be used by the military, firms that use contests for branding or coming up with new products (such as the Four Season’s contest where users are encouraged to take inspiring pictures of Toronto with the

chance of winning free stays), contests run by not-for-profit organizations such as the Hult Prize ([www.hultprize.org](http://www.hultprize.org)) and multi-agents competitions such as the Trading Agent Competition (TAC) (Collins, Ketter, and Sadeh 2010) and the Automated Negotiation Agent Competition (ANAC) (Baarslag and others 2013). Common to all the above examples that the contest initiator is interested in maximizing the expected best contribution (or the  $k$  best contributions) made throughout the contest, quality-wise. As such, the study of contest design, i.e., the relationship between the design of contest and the strategic behavior of contestants, has attracted much attention in recent years, introducing and evaluating different incentive schemes for inducing high quality contributions from utility-maximizing contestants that need to exert costly efforts (Archak and Sundararajan 2009; Cavallo and Jain 2012; Gao et al. 2012).

Alongside the many theoretical contributions made to the field, there is much experimental research aiming at empirically investigating individual behavior in contests (Dechenaux, Kovenock, and Sheremeta 2015). One common finding in this literature is that people tend to exert more effort in contests compared to the theoretical equilibrium-based (as well as alternative model-based) predictions, leading to better expected contributions overall (Sheremeta 2013). This phenomenon was explained primarily by people’s non-monetary utility from winning in a contest (Schmitt et al. 2004; Sheremeta 2010) along with a plethora of secondary explanations such as mistakes and systematic biases (Shupp et al. 2013; Chowdhury, Sheremeta, and Turocy 2014), lack of experience in contests (Sheremeta 2011) and caring about relative payoffs maximization (Mago, Samak, and Sheremeta 2016). All these seem to assume the contest itself is a significant influencing factor.

In this paper we report the results of a set of comprehensive experiments aiming to determine whether indeed more effort is exerted in contests due to the competitive nature of the setting (i.e., because contestants have some utility from “winning”), or perhaps this phenomenon should be attributed to other factors (specifically people’s tendency to risk) that are possibly found also in non-strategic decision settings. Our experiments use a unique design that enables comparing contestants’ decisions in similar decision situations, differing only in whether it is a part of a contest or not.

Our experimental methodology therefore not only compares people’s behavior in contests with the theoretical predictions but more importantly the decisions made by people when in a contest to their decisions in equivalent situations structured in a non-contest context. The decision in both cases should be identical, as long as there is no utility from being declared the winner, as the settings are structured such that in both cases the rewards and odds are identical. Thus, if indeed it is the inherent competitive nature of people that influences their decisions, there should be an apparent gap between the decisions made under the two conditions. To the best of our knowledge, we are the first to suggest such design. Unlike prior work that only speculated about the reasons for over-participation, our unique design enables presenting a hard evidence for lack of any effect related to the contest itself.

For this purpose, we use a “simple” contest model in which contestants only need to strategize about participating in the contest (Ghosh and Kleinberg 2016; Levy, Sarne, and Rochlin 2017; Sarne and Lepioshkin 2017). This contest model (and in particular the fact that a contestant’s strategy is fully captured by her participation decision) offers several inherent advantages that facilitate the studying of whether over-participation in contests derives from the competitive nature of the contest setting or perhaps it is the product of a more general factor that can be found in non-competitive settings. Even more importantly, the use of this contest model enables us generating simple lotteries that capture decision settings equivalent to those faced by some of the subjects in the contests we use, however put in a non-competitive context (as discussed in detail in later sections).

To generalize results, our experimental methodology uses eight contest settings, differing in the nature of the contest used (sequential vs. parallel), the number of contestants (three vs. five) and the participation-rate according to theory (high vs. low). The results, obtained based on the participation decisions of 4000 subjects from Amazon Mechanical Turk (AMT), suggest that indeed, and much like the results reported in prior related work, people tend to over-participate in contests compared to the theoretical equilibrium-based predictions. However, comparing the results obtained in contests to those obtained in the equivalent non-competitive decision settings, we find similar over-participation phenomenon (to a similar extent) in the latter. This last finding, which is not found in prior work due to the absence of comparison to equivalent non-competitive settings, is a major contribution to future designs of methods for eliciting human effort. It suggests that simple lotteries can be used as an effective alternative to contest-based mechanisms, eliciting at least as much effort.

### The Contest Model

The underlying contest model used in our experimental design is similar to the one used by our prior work (Levy, Sarne, and Rochlin 2017) and by Ghosh and Kleinberg (2016) and Sarne and Lepioshkin (2017). Formally, the model considers a contest organizer and a set  $A = \{A_1, \dots, A_k\}$  of  $k > 1$  potential contestants. Each contestant  $A_i$  can either participate in the contest, incurring some cost  $c$ , or opt to avoid participating in the contest. Similar to

our prior work (Levy, Sarne, and Rochlin 2017) and Sarne and Lepioshkin (2017), we assume contestants do not know ahead of time the actual quality of their contributions (i.e., their performance in the contest). Instead, their performance is determined only at the time of the contest, based on some probability distribution function  $f(x)$  (where  $F(x)$  is the corresponding cumulative distribution function). Meaning that the contestants are a priori homogeneous—even though each of them will end up with a different performance at the contest, at the time they make their participation decision none of them has an a priori advantage. The choice of using a priori homogeneous contestants is made for three reasons. First, it eases any calculations contestants may attempt to apply when reasoning about participation in the contest, hence reducing the effect of people’s limited computational capabilities on the results. Second, it eliminates the effect of any envy-like or other emotional considerations resulting from the contestants’ heterogeneity (e.g., if being the underdog). Finally, if contestants are not symmetric at the time of making their decision, each data related to a decision made by a particular contestant must be analyzed based on her type, resulting in an additional possible affecting parameter and requiring collecting an order of magnitude greater amount of data.

The goal of the organizer is to maximize the expected best performance obtained by contestants in a contest it runs. In order to encourage participation in the contest the organizer offers a prize  $M > 0$  to the contestant ranked first (performance-wise) in the contest.<sup>1</sup> In case none of the contestants choose to participate, no prize is awarded and the performance as perceived by the organizer is set to some pre-set fallback performance  $v_0$ .<sup>2</sup> The goal of each contestant is to maximize her own expected profit, defined as the expected prize she is awarded minus the cost incurred if participating in the contest. As in general contest theory literature and in particular in the model we base on, it is assumed that  $f(x)$ ,  $c$  and  $M$  are all common knowledge in the sense that they are known to all contestants and to the organizer (Moldovanu and Sela 2006; Luo, Kanhere, and Tan 2014; Levy, Sarne, and Rochlin 2017).

In this research we consider and experiment with two variants of the above underlying model, differing in the way the contest is designed. The first is based on simultaneous participation (“parallel contest”), i.e., each contestant’s participation decision takes place in parallel to the others’. The second is based on sequential participation (“sequential contest”). Here, each contestant in her turn (according to some pre-defined order) gets to see the results of her predecessors (whether participated, and if so also their performance) and then decides whether to participate in the contest. Our prior work provides a comprehensive equilibrium analysis for both variants of a similar contest model, for the case of fully rational self-interested agents, differing

<sup>1</sup>Since performance is continuous, the chance of having two contestants ranked first is negligible. Otherwise, a tie-breaking rule is required.

<sup>2</sup>As otherwise the expected maximum performance is undefined. Typically the fallback value  $v_0$  will be zero.

only in the way the case where none of the agents choose to participate is handled—while in the current model the prize is not awarded in such case, in the prior model it is awarded to one of the agents with equal probability.<sup>3</sup> This one difference requires minor adjustments to the analysis provided by our prior work and the equilibrium characterization (best-response strategies and expected profits in equilibrium) changes very little. In particular, all proofs use almost identical arguments and algebraic manipulations. Therefore, and since the theoretical analysis is not the essence of this paper, in the following paragraphs we only provide the equilibrium characterization of the two variants in our model, to the extent that enables sufficient insight for understanding the differences in decisions made by people in our experiments compared to the theoretical predictions, and do not include the proofs themselves.

We begin with the parallel contest. Here, we use  $\{P, \neg P\}$  to denote the actions available to each contestant, where  $P$  stands for *participate* and  $\neg P$  for *not participate*. Since the game in this case is simultaneous, every contestant  $A_i$ 's strategy can be captured by the probability  $p_i$  ( $0 \leq p_i \leq 1$ ) she chooses action  $P$  ( $\forall A_i \in A$ ). Since the contestants are a priori homogeneous one equilibrium that necessarily holds is the symmetric equilibrium of the form  $p_i = p \forall i$  ( $0 \leq p \leq 1$ ). This equilibrium, which can coexist alongside pure-strategy equilibria in which some of the contestants participate, is the most natural and fair one and therefore the one we relate to.

Given that all other contestants participate with probability  $p$ , the expected profit of a contestant if participating in the contest, denoted  $B^P$ , is given by:

$$B^P = \sum_{j=0}^{k-1} \binom{k-1}{j} \frac{1}{j+1} M p^j (1-p)^{k-j-1} - c \quad (1)$$

i.e., the contestant is awarded the prize  $M$  whenever her performance is the maximum among all other  $j$  contestants that compete. The expected profit of the contestant if not participating, denoted  $B^{-P}$ , is 0.

The best response strategy of every contestant is thus to participate if  $B^P \geq B^{-P}$  and not participate otherwise. A symmetric Bayesian Nash Equilibrium (BNE) solution  $p$  to the parallel contest should therefore satisfy: (a)  $B^P \leq B^{-P}$  if  $p = 0$ ; (b)  $B^P \geq B^{-P}$  if  $p = 1$ ; and (c)  $B^P = B^{-P}$  if  $0 < p < 1$ .

**Theorem 1** *In the parallel contest case, the BNE is: (a) fully based on pure strategies such that  $p = 1$  (all contestants participate), whenever  $\frac{c}{M} \leq \frac{1}{k}$ ; (b) fully based on pure strategies such that  $p = 0$  (all contestants opt not to participate), whenever  $\frac{c}{M} \geq 1$ ; and (c) based on mixed strategies, otherwise, where  $p$  is the solution to:*

$$\frac{c}{M} = \frac{1 - (1-p)^k}{kp} \quad (2)$$

<sup>3</sup>Our choice of not awarding the prize in case of non-participation simplifies the decision setting to people as otherwise contestants need to take into account that there is a positive expected profit if not competing, rather than zero.

In order to formulate the organizer's expected profit, we make use of the probability that the maximum performance obtained in a contest involving  $k$  contestants is less than  $y$ , denoted  $\bar{F}(y)$ , calculated according to:  $\bar{F}(y) = (pF(y) + (1-p))^k$ . The probability function  $f(y)$  is, by definition, the first derivative of  $\bar{F}(y)$ . The organizer's expected profit, denoted  $B^{org}$ , is thus given by:<sup>4</sup>  $B^{org} = \int_{y=-\infty}^{\infty} \max(v_0, y) f(y) dy - M(1 - (1-p)^k)$ .

Moving on to sequential contest, here the (subgame perfect) BNE is fully in pure strategies, as contestants have perfect information about the performance of preceding contestants. A contestant's strategy  $S$  is her choice of participation given the best performance obtained so far, formally captured by the function  $S : \mathbb{R} \cup \{\emptyset\} \rightarrow \{P, \neg P\}$ , where  $\emptyset$  is the case where all former contestants opted not to participate in the contest. For exposition purposes we align the contestants' participation order with their index (i.e.,  $A_i$  participates before  $A_j$  if  $j > i$ ).

**Theorem 2** *In the sequential contest, the equilibrium solution is: (a) have all contestants not participate whenever  $\frac{c}{M} \geq 1$ ; (b) have all contestants participate whenever  $c = 0$ ; (c) otherwise, have all contestants use the same threshold  $r$  to determine whether or not to participate, where  $r$  satisfies:*

$$\frac{c}{M} = (1 - F(r)) \quad (3)$$

*such that the contestant should participate if and only if the best performance obtained by preceding contestants is lesser than  $r$ .*

If none of the contestants participate, the organizer's expected profit is  $v_0$ . Otherwise, her expected profit is given by:  $B^{org} = \int_{y=-\infty}^{\infty} \max(v_0, y) f(y) dy - M$ , where:

$$\bar{F}(y) = \begin{cases} (F(y))^k & y < r \\ (F(r))^k + \frac{1 - (F(r))^k}{1 - F(r)} (F(y) - F(r)) & y \geq r \end{cases}$$

From the above, it is clear why the a priori homogeneous "simple" contest model used in this paper is an ideal vessel for testing the underlying hypothesis posed: it is a contest by all means (i.e., if people generally benefit from ending up first then this is likely to be reflected in our contest as well) and yet it removes much of the complexities and affecting factors found in traditional contest models. In our model, if contestants were fully rational then their strategies should have been completely symmetric (even in the case of the sequential variant, in equilibrium all contestants follow the same participation rule as prescribed in Theorem 2). Furthermore, in the parallel variant, equilibrium strategies do not depend whatsoever on  $f(x)$  and in the sequential variant the only influence of  $f(x)$  is in mapping the probability corresponding to the indifference between participating and not participating to a performance threshold (meaning that the strategy can also be compactly captured by an accumulated probability threshold, regardless of  $f(x)$ ). In the sequential variant the equilibrium strategy is not even influenced by the number of contestants. All these properties

<sup>4</sup>For the case where  $p > 0$ , as otherwise  $B^{org} = v_0$ .

lead to a clean experimental design, tremendously reducing the space of possible decision states and the possible influence of factors such as one’s position in the sequence or the underlying performance distribution function over the decisions of subjects (at least according to theoretical expectations).

### Experimental Framework

For our experiments we developed a java-script web-based game emulating a “simple” contest of the kind described in the former section. In order to facilitate interaction with a variety of people we used a relatively simple graphic interface and kept instructions simple. Each contestant in the game is told she needs to decide whether to participate or not in a contest with  $k - 1$  other contestants, such that the winner is awarded a bonus of  $M$  cents. Participation does not require any effort (clicking a button) and the performance of a contestant that chooses to participate is immediately determined by the system as a random number (using a uniform distribution function) representing a percentile within the range (0 – 100). Therefore from the contestant’s point of view, the performance measure merely indicates the percentile its contribution falls in rather than its actual value to the organizer. This way we can assign any distribution  $f(x)$  representing the value to the organizer of the contributions obtained, while substantially simplifying the decision situations to contestants (from the computational point of view) as they only need to care about the percentiles (which map to a uniform distribution function between 0 – 100) rather than some complex distribution function. While this latter value has very little influence over the parallel contest, its influence over the sequential contest is immense, as here contestants need to reason about the benefit of participating based on the performance of those participating before them. Our framework therefore saves contestants the trouble of “mapping” the best performance obtained so far to terms of the underlying distribution function.

Prior to making her decision, the contestant is awarded a small payment (e.g., a “bonus” in AMT) of  $c < M$  cents. While participation does not require any effort, as explained above, the participating contestant incurs a cost in the form of losing the initial bonus  $c$  that was awarded. If choosing not to participate in the contest the contestant gets to keep the initial bonus  $c$  and the game ends. The contestant is told that all other contestants are identical in the sense that they are all awarded an initial bonus  $c$  and their performance if participating can put them in any percentile over the range (0 – 100) with an equal chance (i.e., they are all a priori homogeneous).

In the parallel variant of the game contestants need to make their decision based on no additional information, whereas in the sequential variant of the game each contestant is first told her position in the participation sequence and the best performance obtained so far. Once making her decision the contestant gets to see the percentile of her performance (in case of choosing to participate) and the game ends. The ranking of the contestant and consequently her bonus is determined offline, once all other  $k - 1$  contestants completed their turns.

For the alternative decision situation that does not involve a contest we used an even simpler infrastructure. Here, each subject was given the initial bonus  $c$  and had to decide whether to participate in a lottery which awards  $M$  with probability  $p$  and zero with probability  $1 - p$ . In order to participate in the lottery, the participant had to give up the bonus  $c$ . The decision situation in this game captures the exact same decision situation that the last contestant in the sequential contest faces, as in both cases the subject knows the probability of winning  $M$  if choosing to participate.<sup>5</sup> For subjects that are not the last in the sequence of the sequential contest there is no proper way of replicating their exact decision situation through the lottery game—trying to find out experimentally the probability of winning for each performance obtained by prior contestants, based on running sequential contests (i.e., based on observing the behavior of proceeding contestants in the contest game), would require running a substantial number of experiments for every possible performance outcome.

The above lottery game is used also for capturing the decision situation that those participating in the parallel contest are facing. Here, we have a similar basic lottery. For the winning probability we use either: (a) the probability of winning based on assuming all other subjects are completely rational, i.e., based on Theorem 1; or (b) the probability of winning calculated based on the participation rate observed in experiments run with the contest game. We used both, i.e., running both types of experiments for the parallel contest equivalent.

### Experimental Design

We used eight experimental treatments, each corresponding to a different combination of the contest type (sequential and parallel), the number of contestants (3 and 5), and the theoretical predictions for the participation probability (high and low participation thresholds in the sequential contest and high and low participation probability in the parallel contest). The prize  $M$  and cost  $c$  values for each treatment are given in table 1.

# of Contestants		Sequential	Parallel
3	H	$M = 10\phi, c = 4\phi$	$M = 7\phi, c = 4\phi$
	L	$M = 5\phi, c = 4\phi$	$M = 5\phi, c = 4\phi$
5	H	$M = 10\phi, c = 4\phi$	$M = 10\phi, c = 4\phi$
	L	$M = 5\phi, c = 4\phi$	$M = 6\phi, c = 4\phi$

Table 1: Experimental treatments used in the experiments.

The participation cost was set to be constant to provide a similar baseline to all treatments. When setting the prize  $M$  we aimed for two levels of participation according to the theoretical predictions. Consequently, the  $M$  values in the “high” (“H”) treatments correspond to a participation threshold of  $r = 60$  (both with 3 and 5 contestants) in the sequential contest (according to (3)) and a participation probability of  $p = 0.51$  and  $p = 0.48$  in the parallel contest (according

<sup>5</sup>Here  $p$  is the chance of being placed in a percentile greater than the highest observed so far.

to Theorem 1), for 3 and 5 contestants, respectively. The  $M$  values in the “low” (“L”) treatments correspond to a participation threshold of  $r = 20$  (both with 3 and 5 contestants) in the sequential contest and a participation probability of  $p = 0.2$  (both with 3 and 5 contestants) in the parallel one.

Subjects were recruited and interacted through AMT which has proven to be a well established method for data collection in tasks which require human intelligence (Paolacci, Chandler, and Ipeirotis 2010). To prevent any carry-over effect a “between-subjects” design was used, assigning each participant to one treatment only (either in its contest or lottery form). The compensation for taking part in the experiment included a small show-up fee (the basic “HIT”) but mostly relied on the bonus awarded.

Each subject received thorough instructions of the game rules, the compensation terms and her goal in the game. Prior to starting the game subjects had to correctly answer a short quiz, making sure they fully understand the game and the compensation method. Finally, subjects had to play a single-shot game (i.e., make one decision). We emphasized to subjects that choosing to participate or not to participate in the contest (or lottery) will not affect their basic payment for the HIT—only the preliminary bonus  $c$  awarded and the potential bonus  $M$  offered are affected by this decision.

The set of experiments aiming to test individual behaviors in similar non-contest decision situations where carried out after completing the contests, as we needed to calculate the experimental chance of winning for the parallel contests as explained in the former section. The comparison to parallel contests used the results obtained in the former stage. For comparing behaviors to those reflected by the last contestants in the sequential contest, however, we had to substantially augment the pool of observations as the natural course of competition resulted in having most of the best performance values observed by the last contestant in a very narrow interval. Therefore in order to get a richer comparison, we ran additional experiments where we randomly picked the best performance to be presented to the last contestant and used it as the input for subjects, telling them they are the last contestant. Then we experimented with similar decision situations using the lottery framework.

Overall, we had 4000 participants taking part in our experiments: 2000 competing in contests, 1200 choosing whether or not to participate in lotteries replicating decision-situations similar to those experienced in contests and 800 competing as the third or fifth contestants in contests (for augmenting the space of contest-related decisions that can be emulated by lotteries). A more detailed breakdown is provided in the following section. Subjects ranged in age (21-70), gender (50% men and 50% women) and education, with a fairly balanced division between treatments.

## Results

In this section we summarize the results obtained and their analysis. Statistical significance, whenever applicable, was calculated using the t-test (for means) and z-test (for proportions). In case none of the participants chose to participate we took the profit to be zero (i.e.,  $v_0 = 0$ ).

## Non-contests vs. Contests Comparison

Table 2 compares the empirical participation-rate obtained when putting subjects in the exact same decision situations in lotteries and sequential contests. Each reported result corresponds to decisions made by 100 different subjects.<sup>6</sup> The third column relates to settings where according to theory contestants should have participated (i.e., the best performance percentile achieved prior to participation or the lottery’s winning chance was less than 60% and 20% in the “H” and “L” conditions, respectively) and participated in practice. The fourth column relates to settings where according to theory contestants should not have participated and yet participated in practice. As can be seen from the table both in the competitive (contest-based) and non-competitive (lottery-based) settings almost all participants participate when they should, and a surprisingly high percentage of people participate even when they should not. The results of contests and lotteries are very close and in fact for all pairs the difference is found to be non-statistically significant ( $p_{z-test} > 0.08$ ). Meaning that the same over-participation phenomena holds in both cases, and to the same extent.

# of Contestants		Should participate and do		Should not participate but do	
		lottery	contest	lottery	contest
3	H	92%	92%	60%	48%
	L	82%	88%	59%	56%
5	H	92%	91%	60%	58%
	L	82%	86%	59%	56%

Table 2: Participation rate in similar decision situations of sequential contests and lotteries.

Table 3 presents a similar comparison, however for decision situations experienced with parallel contests. Each reported result corresponds to decisions made by 100 subjects. The values in the third column relate to the empirical participation rate found in the contest (detailed in the following subsection). The fourth and fifth columns present the participation rate obtained in non-contest decision situations where the winning probabilities were taken to be those that hold in the parallel contest when calculated according to the theoretical predicted participation probability and the participation rate observed in the parallel contest, respectively. Here, once again, we obtain that subjects’ behavior when put in a similar decision situations, however in a non-contest context, are very close to those obtained in the equivalent contest situation. All differences, besides two, between pairs of an empirical participation rate in contests and its corresponding rate in equivalent lotteries (when using either winning probability calculation method) were found to be non-statistically significant ( $p_{z-test} > 0.06$ ). Even in the two cases where the difference was found to be statistically significant, it was the lotteries where a greater participation rate was found. Therefore, we conclude that the

<sup>6</sup>Except for the lottery results, where the number of participants is irrelevant and therefore we could use the same results for comparing with contests of both 3 and 5 contestants.

over-participation phenomenon is of a similar magnitude in the competitive and non-competitive settings, and possibly even to a lesser extent in parallel contests.

# of Contestants		Empirical	Validation (empirical participation)	Validation (theoretical participation)
3	H	76%	79%	85%
	L	52%	55%	78%
5	H	74%	62%	79%
	L	58%	59%	82%

Table 3: Participation rate in similar decision situations of parallel contests and lotteries.

### Over-participation in Contests

Table 4 provides a comparative analysis of contestants’ participation rate in the sequential contest for the four different combinations of number of contestants and the theoretical participation predictions. The third column depicts the percentage of contestants out of those placed first in the contest sequence that chose not to participate. According to theory, a rational contestant aiming to maximize its expected profit should always choose to participate in all sequential contest treatments if placed first in the sequence. Therefore, having a non-negligible percentage of the first contestants not participate in the contest is likely to result in a degradation in the organizer’s average profit compared to theory. Still, in those cases the organizer can simply terminate the current contest and initiate a new one, without incurring any loss as that first contestant is not eligible for a prize.<sup>7</sup>

# of Contestants		First who do not participate	Should participate and do	Should not participate but do
3	H	18%	93%	47%
	L	30%	77%	50%
5	H	24%	83%	47%
	L	48%	63%	47%

Table 4: Participation rate in the sequential contest according to the three measurable behaviors detailed in the main text.

The fourth and fifth columns use a division similar to the one used in Table 2. In the fourth column we observe that in both treatments the great majority of contestants indeed make the right participation decision whenever they are supposed to participate, which again is likely to cause some degradation in the organizer’s average profit in practice compared to theory. In the fifth column, we see that in both treatments almost half of the participants decided to participate, resulting in an increase in the best performance obtained, compared to the theoretical analysis. As expected,

<sup>7</sup>In contrast, terminating the contest after the first contestant participates is not legitimate as the first contestant has already spent some time and resources on participation based on knowing that the prize will be awarded according to the contest rules.

# of Contestants		Participation probability (theory)	Participation rate (empirical)	Best Response (based on empirical)
3	H	51%	76%	$\neg P$ (i.e., 0%)
	L	20%	52%	$\neg P$ (i.e., 0%)
5	H	48%	74%	$\neg P$ (i.e., 0%)
	L	20%	58%	$\neg P$ (i.e., 0%)

Table 5: Participation rate in the parallel contest.

the participation percentage increases as the number of contestants decreases and the theoretical participation threshold increases, in all three cases analyzed in Table 4. Interestingly, we find that the effect of over-participation does not depend on a contestant’s position, aligning with Theorem 2.

Overall, the results suggest a substantial advantage to running the contest with people compared to the theoretical predictions, as far as the organizer’s profit is concerned—the organizer can overcome the decreased participation rate of those placed first simply by restarting the contest, suffers a small loss due to the decrease in the percentage of those who should have participated and do not, however gains substantially from the high participation rate among those who are not supposed to participate according to the theory. Consequently, we observe an increase in the organizer’s average profit in our experiments with sequential contests compared to theory. The magnitude of improvement and its significance depend on the distribution of performance  $f(x)$  as explained in the contest model section. For example, with three contestants, when  $f(x)$  is uniform over the interval  $(0, 100)$  we obtain a non-statistically-significant improvement for the “H” case and a substantial statistically-significant improvement for the “L” case. If  $f(x)$  is a decreasing linear function over the interval  $(0, 100)$ , e.g., going from 0.02 to 0, we obtain a substantial statistically-significant improvement for both the “H” and “L” cases.

Table 5 presents the results obtained for the parallel contest. The third column depicts the participation probability anticipated by theory and the fourth column depicts the percentage of contestants who chose to participate in the contest in our experiments with the parallel contest. Indeed, in all cases contestants were found to be more eager to participate in the contest compared to the equilibrium participation probability ( $p_{z-test} < 0.01$ ). To put the results in context, we provide in the fifth column of the table the optimal participation decision given that all other contestants use the empirical participation rate. Interestingly we find that the best response strategy given the empirical participation rate is 0%, i.e., it is better not to participate ( $B^{-P} > B^P$ ). Here, the increased participation rate results in a substantial statistically-significant increase in the organizer’s expected profit compared to theory.

### Related Work

Contests are organizational structures in which contestants spend costly efforts (e.g., time, resources) to win one or more prizes (Dechenaux, Kovenock, and Sheremeta 2015). Contest design, i.e., the set of rules that define a contest, had

focused much interest in literature (Dasgupta and Nti 1998; Ghosh and Kleinberg 2016), differing primarily in the assumptions made in the underlying contest model (e.g., offering several prizes (Archak and Sundararajan 2009; Cavallo and Jain 2013) or using more than a single stage (most commonly in the form of a tournament) (Clark and Riis 1998; Gradstein and Konrad 1999)) and the contest organizer's goals (e.g., maximizing overall effort, best effort, fairness) (Lewenberg et al. 2013).

Much effort has been devoted to empirically investigate people's behavior in contests in general (Sheremeta 2011; Liu et al. 2014; Dechenaux, Kovenock, and Sheremeta 2015) and in crowdsourcing contests in particular (Yang, Adamic, and Ackerman 2008), comparing the behaviors observed with theoretical predictions and suggesting efficient contests designs for the case of human contestants. Among the factors studied under that framework are the number of contestants (e.g., Boudreau and Lakhani (2011) provided empirical confirmation (using TopCoder) that adding contestants shifts expected performance downward and Garcia and Tor (2009) provided some evidence of an effort-reducing impact as the number of contestants increase), number of prizes (finding various effects related to the number of prizes and their allocation methods over efforts induced and principal's profit (Lazear 2000; Harbring and Irlenbusch 2003; Kazai 2011)), contestants' heterogeneity (e.g., Yang et al. (2008) showed that prospective contestants on Taskcn.com tend to select tasks with fewer opponents and higher expected rewards, Kazai (2011) investigated the effect of worker qualifications on the quality of the output in tasks crowdsourced through AMT), and the provision of feedbacks throughout the contest (e.g., Yang et al. (2009) showed that by providing qualitative feedbacks, solvers were encouraged to exert much more efforts, as probability of winning perceived by solvers can be increased.)

In particular, much prior work has been devoted to providing empirical support for people's over-expenditure of effort compared to theoretical predictions (Potters, de Vries, and van Winden 1998; Anderson and Stafford 2003; Sheremeta 2011; 2013).<sup>8</sup> The reasons proposed for this phenomenon are diverse (Dechenaux, Kovenock, and Sheremeta 2015). The most common reason is that subjects derive a non-monetary utility from winning in addition to monetary incentives (Schmitt et al. 2004; Parco, Rapoport, and Amaldoss 2005; Sheremeta 2010). Other reasons provided suggested that subjects are driven by spiteful preferences and inequality aversion (Bartling et al. 2009; Balafoutas, Kerschbamer, and Sutter 2012), that subjects care about their relative payoffs maximization (Fonseca 2009; Mago, Samak, and Sheremeta 2016), that they are prone to mistakes and systematic biases and lack experience (Sheremeta 2011; Chowdhury, Sheremeta, and Turocy 2014) and, as appear in many of the works cited above, that they are influenced

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<sup>8</sup>In that context it is worth mentioning the work of Boudreau, and Lakhani (2011) that found that in TopCoder.com, when enabling people to choose whether to work cooperatively or competitively, those who preferred to work in a competition exerted much more effort.

by all kinds of aspects related to the contest structure (e.g., number of contestants, number of prizes, heterogeneity of contestants).<sup>9</sup>

Common to all the above, that they consider contest-related factors as arguments for over-participation. Furthermore, the hypothesis that this has very little to do with the competitive nature of contest simply could not have been tested in these studies as none has used an experimental design aiming to compare the behaviors observed in contests to those reflected in equivalent non-competitive decision situations as in the current study.

## Conclusions and Future Research

Much like with the results reported for effort-based contests in literature, we find that in "simple" contests people tend to exert more effort as contestants compared to the theoretical equilibrium expectations. In our case this is reflected by the excessive participation rate, which maps to willingness to incur a cost that does not justify the expected rewards offered. In that sense, "simple" contests are a perfect fit for studying whether the exertion of more effort in contests should be attributed to the competitive nature of the setting. Our unique experimental design, however, enables an important insight that is absent in prior work - it is not the competitive nature of the interaction that accounts for the excessive effort exerted, as speculated in prior work, but rather some other factor that holds also in non-competitive similar decision settings, most probably people's tendency towards risk. This insight is supported by direct comparison of decisions made in contests and in equivalent decision situations from which the competitive aspect is absent, and is of great importance to mechanism designers as it implies the use of simple lotteries as an effective alternative to (rather complex to coordinate) contests.

While the above conclusions are based on eight settings differing in the type of contest used, the number of contestants and the theoretical participation-rate predictions, in order to adequately generalize the results much further experimentation is required. In particular, unlike with the case of the parallel contest where complete coverage was achieved, in the sequential contest only the decisions of the last contestants were compared to their non-competitive equivalent. Finding an appropriate non-competitive equivalence to all decision situations is challenging, especially as far as simple lotteries of the type we use in our experiments are concerned. While we have every reason to believe that the same phenomenon holds in sequential contests also with the decisions for which we did not have an equivalent lottery in the non-competitive setting, we do hope that future research will come up with alternative approaches enabling validation. In that sense, other researchers can benefit greatly from the experimental methodology reported in the paper, when carrying out this kind of research.

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<sup>9</sup>This aligns in general literature dealing with people's bounded rationality (Kahneman 2000; Levy and Sarne 2016).

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