Races or Tournaments? [PRELIMINARY AND INCOMPLETE]*

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Last updated: 11 April, 2017

Abstract

Contests are often used as incentive schemes to foster innovation. The typical goal of contest designers is to maximize quality while minimizing the time it takes to achieve the innovation. This situation leads to a difficult choice of design made under considerable uncertainty. In this study, we investigate one key aspect of this decision that is the way participants compete. Two extreme forms of competition are considered: the race, where the first to achieve the innovation wins, and the tournament, where the timing is not important. We develop a model to characterize under what conditions contest designers should go for one or the other approach. Then, we report the results of a field experiment conducted to compare the outcomes of three alternative competitive situations motivated by theory: the race, the tournament, and the tournament with a quality requirement. We find that outcomes in a race are of comparable quality, but are supplied faster. Based on our model, we also show what would be optimal to do under several simulated counterfactual situations.

JEL Classification: xxx; xxx; xxx.

Keywords: xxxx; xxxx xxxx.

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1 Introduction

Organizations often use contests as incentive schemes to foster innovation. In an innovation contest, participants compete for prizes by investing time and energy in an innovation project. The typical aim of the contest designer is to maximize quality while minimizing the time to complete the innovation. Balancing between these two desirable but incompatible features it is often difficult. The lack of knowledge about individual costs and technical feasibility of the innovation may force contest designers to make their choices under considerable uncertainty. A growing literature on contest design offers insights on how to make better resolutions. However, while researchers have examined various aspects of managing this trade-off, the optimal design is still largely unknown.

Here, we investigate one key aspect of contest design concerning the way participants compete. There are two extreme forms of competition that we consider. One is the *race* where the first to finish an innovation project wins. The second is the *tournament* where the best finished project wins. To fix ideas, imagine a government designing an innovation contest to find a solution to a threat to the public health, such as the UK government on the problem of antibiotic resistance.[1] To minimize the risks that the threat will materialize before a solution is found, one choice is a tournament competition with a tight deadline for participants to provide their solutions. Alternatively, the government can use a race competition awarding a prize to the first participant that achieves, or goes beyond, a minimum effectiveness threshold. Fixed the prize, both approaches have specific advantages and limitations. If the duration of the competition is too low, a tournament may give insufficient incentives resulting in inadequate solutions. In a race competition, instead, timing is not an issue but participants have no incentives to exceed the minimum threshold.

In the present study, we shed light on the conditions under which contest designers should choose between a race and a tournament competition. We proceed in two ways. First, we develop a contest model that encompasses both the race and the tournament in a single framework. Exploring the duality of the model, we compare equilibrium behaviors under both regimes and characterize the optimal choice (i.e., the setup that maximizes the utility of the contest designer). Then, we design and execute an experiment to test the implications of the theory in the field, providing policy recommendations.

Regarding to the modeling, we adapt the contest model introduced by **?**. Contests have an all-pay structure by which participants pay an immediate cost for an uncertain future reward. We generalize by allowing participants to choose the timing and quality

[1] This example is taken...

of the innovation at once. This decision is made under the uncertainty of the costs of the rivals, which are privately observed by the agents. The contest designer is modeled as an extra agent with preferences for both time and quality. Following the analysis of the model model, we show that the optimal design depends on the number of participants and the concavity of their cost function.

The field experiment was conducted at the end of 2016. The context of the experiment was an online programming competition. In a programming competition, participants compete writing source code that solves a given problem for winning a monetary prize. We worked together with researchers from the United States National Health Institute (NIH) and the Scripps Research Institute (SCRIPPS) to select a challenging problem for the contest. The selected problem was based on an algorithm called BANNER built by NIH (**?**) that uses expert labeling to annotate abstracts from a prominent life sciences and biomedical search engine, PubMed, so disease characteristics can be more easily identified. The goal of the programming competition was to improve upon the current NIH's system by using a combination of expert and non-expert labeling, as described by **?**. The competition was hosted online on the platform Topcoder.com (about 1M registered users in 2016). Top submissions were awarded monetary prizes ranging between $100 to $5000 for a total prize pool of more than $40,000.

Our intervention consisted in sorting at random participants into independent virtual rooms of 10 or 15 people. These virtual rooms were then randomly assigned to one of three different competitive settings: a race, a tournament, and a tournament with a reserve score, which is the lowest acceptable score by the platform for a submission to be awarded a prize.

We find that xxxxx [participation in the tournament is xxx compared to the race the reserve.]

We also find that xxxx [submission are quicker in a race, whereas are equally distributed at the end of the competition in the the tournament and in the tournament with quality requirement.]

Another interesting finding is that xxxxx [No evidence trade-off between a race and a tournament in terms of higher scores vs faster submissions. We do find that scores are higher in the tournament but we do not find a strong trade-off in the sense that race had comparable good quality solutions than the tournament.]

2 Literature

This paper is related to the contest theory literature **?** **?**, **?**, **?**, **?**, **?**, **?**. It also relates to the literature on innovation contests **?**, **?**. And the personnel economics approach to contests **?**, **?**, **?**.

Empirically, **?** provide a comprehensive summary of the experimental literature on contests and tourments. Large body of empirical works have focused on sports contests **?**. More recently, inside firms (xxx) and online contest (xxxx).

This paper is also related to the econometrics of auctions **?**, **?**, **?** and more recently **?**, **?**, and **?**.

An extensive literature has discussed the reasons why contests are sometimes preferred to other forms of incentives (e.g., individual contracts). Typically, contests reduce monitoring costs [xxx], incentivize production with common risks [xxx], and deal with indivisible rewards [xxxx], among others. While there is not much debate on why contests should be used, the issue of how to effectively design and deploy a contest still attracts much research.

Several aspects of contest design have been investigated, including the optimal prize structure [XXX, xxxx, xxxx], number of competitors [XXX, XXX], and imposing restrictions to competition such as minimum effort requirements [XXX, XXX]. Also, a great deal of theoretical models of races and tournaments have been developed and applied to a wide range of economic situations including patent races [xxx], arms races [xxx], sports [xxx], the mechanism of promotions inside firms [xxxx], sales tournaments [xxxx], etc.

?, **?** investigate the dynamics issues patent races where the interest is how firms compete for a patent. **?** looks at the problem of how to design an information structure that is optimal when the contest is a race and innovation is uncertain (encouragement and competition effect). In the laboratory, **?** finds poor support to predictions of dynamic xxxx. In general we do not know much about the dynamic aspect of contests.

The duality. As pointed out by **?**, many of these models of tournament and race competitions are specific cases of a more general "contest games." And sometimes it is possible to design one or the other in a way to exploit a "duality." In other words, in theory, a competition can be designed as a tournament to do xxx or as a race to do xxx. While theoretically very useful, how to exploit this duality in practice remains largely unknown. Lack of data. As before, xxxx. The main challenge is self-selection. The answer to this optimal design question relates to the cost function of agents with respect to "time" and to "effort." It is hard to say which solution is better. However, it is easier to tell whether you should have one prize or multiple prizes.

3 The model

In this section, we generalize the *contest game* introduced by **?** to a situation where players allocate their effort along two dimensions: quality and time to complete a given job. Then we explore the problem of maximization faced by a contest designer with preferences for both quality and time.

3.1 Basic setup

A (generalized) contest game is an n player game with asymmetric information. Each player ($i = 1, ..., n$) competes for multiple prizes by choosing a performance variable y_i and a timing t_i both nonnegative numbers. Players hold a valuation v_k that assignes a nonnegative value to each prize ($k = 1, ..., q$) with $v_1 \geq v_2 \geq ... \geq v_q$.

Players move simultaneously to maximize the probability of winning a prize while minimizing the cost of effort. Costs are known up to an individual ability parameter a_i that is private information of each player and is drawn at random from a common distribution $F_{\mathcal{A}}$ on the finite interval $\mathcal{A} = [\underline{a}, \bar{a}]$.

Player i's cost function is

$$C(a_i, y_i, t_i) = c_a(a_i)c_y(y_i)c_t(t_i) \tag{1}$$

with $c_a(\cdot)$ and $c_t(\cdot)$ being monotonic decreasing functions (the higher the ability or the time to complete, the lower the cost) and $c_y(\cdot)$ being a monotonic increasing function (the higher the quality, the higher the cost). We further impose conditions to ensure nonnegative costs: $c_a(\bar{a}) > 0$, $\lim_{t\to\infty} c_t(t) > 0$, and $c_y(0) \geq 0$.

Let $p_{i,k}(y_1, ..., y_N, t_1, ..., t_N)$ be player i's probability of winning the k^{th} prize. Player i's expected payoff is

$$\pi_i = \sum_{k=1}^{q} p_{i,k}(y_1, ..., y_N, t_1, ..., t_N)v_k - C(a_i, y_i, t_i). \tag{2}$$

A generalized contest game G can be then denoted by

$$G \equiv \left\{n, q, \{v_k\}_{k=1}^{q}, F_{\mathcal{A}}, C, \{p_{i,k}\}_{i,k=1}^{q,n}\right\}. \tag{3}$$

The game G is said to have minimum-entry requirements when it is not sufficient to beat the other competitors to win a prize but players have also to successfully meet a given deadline and/or satisfy a minimum quality requirement. Let $\bar{t} > 0$ denote the deadline and $\underline{y} \geq 0$ the required minimum performance. A game G has minimum-entry requirements when, for every prize k and player i, the probability $p_{i,k}(\cdot,\cdot) = 0$ when player i's quality is below a target level $q_i < \underline{y}$ or the timing to completion is above a given deadline $t_i > \bar{t}$.[2]

The tournament corresponds to a special case in which players have a deadline to meet and the player having achieved the highest output quality within the deadline gets the first prize, the player having achieved the second highest output quality gets the second prize, and so on. This is formally defined in Definition 1 below.

Definition 1. *Let $y_{(1:n-1)}, \ldots, y_{(n-1:n-1)}$ denote the order statistics of the y's for player i's $n-1$ opponents. A tournament is a contest game G with a minimum-entry requirement $\bar{t}$ where player i's probability of winning a prize is*

$$p_{tour,i,k} = \begin{cases} \Pr(y_i > y_{n-1:n-1}) & \textit{if } k = 1 \\ \Pr(y_{n-k+1:n-1} > y_i > y_{n-k:n-1}) & \textit{if } k > 1. \end{cases} \tag{4}$$

That is, in a tournament, player i's probability of winning the kth prize is simply the probability of player i's quality being smaller than the $n-k+1$'s and greater than the $n-k$'s order statistic of the y's.

Likewise the race corresponds to a special case where the player being the first to complete a job with a minimum quality gets the first prize, the player being the second to complete a job with a minimum quality gets the second prize, and so on. Hence, the following definition.

Definition 1. A race is a contest game G with minimum-entry requirements $\underline{y}$ where player i's probability of winning a prize is

$$p_{\text{race},i,k} = \begin{cases} \Pr(t_i < t_{1:n-1}) & \text{if } k = 1 \\ \Pr(t_{1-k:n-1} > t_i > t_{k:n-1}) & \text{if } k > 1. \end{cases} \tag{5}$$

That is, in a race xxxxx.

3.2 Equilibrium

To simplify the analysis, suppose there are only two prizes of total value normalized to one. Let $\alpha \geq 1/2$ denote the fraction of total prizes going to the first placed competitor with $1-\alpha$ going to the second placed competitor.

[2]We further use the convention that whenever $t_i > \bar{t}$ then $y_i = 0$ and whenever $y_i < \underline{y}$ then $t_i = \infty$. This simply means that when one of the entry-requirements is not met players xxxxx.

Let first focus the analysis on the case of a tournament.

First, notice that picking a completion time equal to the deadline ($t_i^* = \bar{t}$) is a (weakly) dominant strategy for each player. This is because, while each player finds costly to lower the time to complete a job, the probability of winning a prize is not affected by the completion time as soon as the deadline is met.

Fixing $t_i^* = \bar{t}$ for each player works like a uniform increase in the marginal costs that is equal to $c_t(\bar{t})$. Alternatively, it can be seen as a uniform reduction in the total value of prizes by a factor of $1/c_t(\bar{t})$. In this case, the minimum-entry requirement does not reduce the number of participating competitors.

Following **?**, the (unique) symmetric XXXX equilibrium for player i's quality is

$$c_y^{-1}\left[c_y(\underline{y}) + \frac{1}{c_t(\bar{t})}\left(\alpha\int_{a_i}^{\bar{a}} A(z)dz + (1-\alpha)\int_{a_i}^{\bar{a}} B(z)dz\right)\right] \tag{6}$$

where

$$A(x) = \frac{1}{c_a(x)} F'_{(n-1:n-1)}(x) \tag{7}$$

and

$$B(x) = \frac{1}{c_a(x)}\left\{\left[1 - F_{(n-1:n-1)}(x)\right] F'_{(n-1:n-2)}(x) + F'_{(n-1:n-1)}(x) F_{(n-1:n-2)}(x)\right\}. \tag{8}$$

This equilibrium strategy is obtained by solving the first-order differential equation:

$$\begin{aligned}0 =& \alpha F'_{(1:N-1)}(\phi)\phi' + \\ &+ (1-\alpha)\phi'\left\{\left[1 - F_{(1:N-1)}(\phi)\right] F'_{(1:N-2)}(\phi) + F'_{(1:N-1)}(\phi) F_{(1:N-2)}(\phi)\right\} + \\ &- c_a(a) c_y(\underline{y}) c_t'(t_i)\end{aligned} \tag{9}$$

with boundary condition $xxxx$.

Race. In a similar way, we derive the xxxx in a race. Clearly, any positive quality that is below the minimum-entry requirement will raise costs while giving a zero probability of winning. Thus, player i's choice of optimal quality y_i^* is binary. Either $y_i = 0$ (with $t_i = \bar{t}$ by convention) or $y_i = \underline{y}$.

$$c_t^{-1}\left[c_t(\bar{t}) + \frac{1}{c_y(\underline{y})}\left(\alpha\int_{a_i}^{\infty} ...dz + (1-\alpha)\int_{a_i}^{\infty} ...dz\right)\right] \quad \text{if } a_i \geq \hat{a}. \tag{10}$$

APPENDIX. Consider player i's choice and suppose that the other $N-1$ players use the equilibrium strategy stated in the proposition. Let $\phi = t^{-1}$ denote the inverse of the optimal bidding function. Player i's best response is a timing t_i and performance y_i that maximize the expected payoffs (2) given the other players' equilibrium.

Any $y_i > \underline{y}$ or $0 < y_i < \underline{y}$ will raise costs while leaving unchanged the probability of winning. Thus, the choice of y_i is binary. Either $y_i = 0$ (with $t_i = \bar{t}$ by convention) or $y_i = \underline{y}$.

Suppose $y_i = \underline{y}$. The optimal t_i maximizes the expected payoffs. To compute the expected payoff we use the following notation. For any sequence of variables $x_1, ..., x_{N-1}$, let $x_{(1:N-1)}, ..., x_{(N-1:N-1)}$ denote the $N-1$ order statistics of the x's, and let $F^x_{(1:N-1)}, ..., F^x_{(N-1:N-1)}$ be the corresponding distribution function. Then the probability of winning a prize (**??**) becomes:

$$\begin{aligned} p_{i,1}(y_1, ..., y_N; t_1, ..., t_N) &= \Pr(t_i \leq t_{(1:N-1)}) \\ &= \Pr(t_i \leq t^*(a_{(1:N-1)})) \\ &= \Pr(\phi(t_i) \geq a_{(1:N-1)}) \\ &= F^a_{(1:N-1)}(\phi(t_i)). \end{aligned} \tag{11}$$

$$\begin{aligned} p_{i,2}(y_1, ..., y_N; t_1, ..., t_N) &= \Pr(t_{(1:N-1)} < t_i \leq t_{(2:N-1)}) \\ &= \Pr(t_i \leq t_{(1:N-1)} \mid t_{(1:N-1)} < t_i) \Pr(t_{(1:N-1)} < t_i) \\ &= \Pr(\phi(t_i) \geq a_{(1:N-1)} \mid a_{(1:N-1)} > \phi(t_i)) \Pr(a_{(1:N-1)} > \phi(t_i)) \\ &\quad \text{(using the independence of individual abilities)} \\ &= F^a_{(1:N-2)}(\phi(t_i)) \left[1 - F^a_{(1:N-1)}(\phi(t_i))\right]. \end{aligned} \tag{12}$$

Using (11) and (12) with (2), player i's expected payoff is (to simplify notation, we drop the index a on the distribution of the order statistics of the individual abilities)

$$\alpha F_{(1:N-1)}(\phi(t_i)) + (1-\alpha) F_{(1:N-2)}(\phi(t_i)) \left[1 - F_{(1:N-1)}(\phi(t_i))\right] - c_a(a_i) c_y(y_i) c_t(t_i). \tag{13}$$

The first order condition for a maximum (see **?**) is

$$\begin{aligned}0 =&\alpha F'_{(1:N-1)}(\phi)\phi' + \\ &+ (1-\alpha)\phi'\left\{\left[1-F_{(1:N-1)}(\phi)\right]F'_{(1:N-2)}(\phi) + F'_{(1:N-1)}(\phi)F_{(1:N-2)}(\phi)\right\} + \\ &- c_a(a)c_y(\underline{y})c'_t(t_i).\end{aligned} \tag{14}$$

Using $\phi' = 1/t^{*\prime}(\phi)$ and the equilibrium $\phi(t_i) = \phi(t^*(a_i)) = a_i$, leads to

$$\begin{aligned}c'_t(t^*(a_i))t^{*\prime}(a_i) =& \frac{\alpha}{c_a(a)c_y(\underline{y})}F'_{(1:N-1)}(a_i) + \frac{(1-\alpha)}{c_a(a)c_y(\underline{y})}\times \\ &\times\left\{\left[1-F_{(1:N-1)}(a_i)\right]F'_{(1:N-2)}(a_i) + F'_{(1:N-1)}(a_i)F_{(1:N-2)}(a_i)\right\}.\end{aligned} \tag{15}$$

This gives a differential equation with boundary conditions $t^*(\hat{a}) = \bar{t}$. Integrating both sides and using the integration rule $\int h(g(x))g'(x)dx = H(g(x)) + A$ (where $H(\cdot)$ is the antiderivative of $h(\cdot)$ and A is an arbitrary constant) leads to

$$c_t(t^*(a_i)) = A + \frac{\alpha}{c_y(\underline{y})}\int A(x)dx + \frac{(1-\alpha)}{c_y(\underline{y})}\int B(x)dx \tag{16}$$

where

$$A(x) = \frac{1}{c_a(x)}F'_{(1:N-1)}(x)$$

and

$$B(x) = \frac{1}{c_a(x)}\left\{\left[1-F_{(1:N-1)}(x)\right]F'_{(1:N-2)}(x) + F'_{(1:N-1)}(x)F_{(1:N-2)}(x)\right\}.$$

Then we pin down the marginal type $\hat{a}$ by imposing the zero profit condition

$$\begin{aligned}\pi_i =&\alpha\left[1-F_{(1:N-1)}(\hat{a})\right] + (1-\alpha)\left[1-F_{(1:N-2)}(\hat{a})\right]F_{(1:N-1)}(\hat{a}) + \\ &- c_y(\underline{y})c_a(\hat{a})c_t(\bar{t}) = 0.\end{aligned} \tag{17}$$

[Correction: it is not 1:N-1 but N-1:N-1]

Clearly, when $\hat{a}$ goes to infinity (costs go to zero), the probability that the N-1'th order statistics will be higher then xxx becomes zero. Hence, the payoff becomes $\alpha \geq 0$. If instead $\hat{a}$ goes to zero, then payoffs are negative. Hence, there is alpha in the middle... (need to show it is concave). □

An important property of xxx is that $y^*(a_i)$ has its upper bound in xxx and lower bound in xxxx. Also, equilibrium output quality is monotonic increasing in the agent's ability (see **?**). Thus, for every $i = 1, ..., n+1$, the equilibrium expected reward depends only on the rank of his ability relative to the others. Using $F_{A_{r:n}}$ to denote the distribution of the r'th order statistic of abilities gives

$$F_{A_{n:n}}(a_i)V_1 - C(y_i^*, d, a_i). \tag{18}$$

Hence, by setting to zero and solving for the ability, gives the marginal ability $\underline{a}$ as

$$\underline{a} = h(n, V, F_A, C, d). \tag{19}$$

The equilibrium in a tournament is stated below.

Proposition 1. *In a tournament, xxxx*

By comparing xxx and xxx, we find that xxxx.

Proposition 2. *Let target xxx be higher in a race than in a tournament.Then, there always exist a non-empty set of abilities $\mathcal{A}_0 \subset \mathcal{A}$ where players in the race generate higher performance than in the tournament.*

Proof. Marginal type has utility zero in a race but the same type has a strictly positive utility in the tournament. Since probability of winning is not different in the race or the tournament (the bid is a monotonic transformation of the individual ability or, in other words, rankings are virtually the same), expected payoffs in equilibrium differ only in the cost functions. Hence, to be an equilibrium, the player in the tournament should bid less than the player in the race to earn a strictly positive expected payoff. □

Let's make an example. Suppose xxxx.

```
p <- plnorm   # pdf individual abilities
r <- rlnorm   # Simulate individual abilities
cy <- function(x) x^2 # Cost function performance
ct <- function(x) 2*exp(1-x)  # Cost function timing
```

FIGURE 1. Equilibrium bids in a race and a tournament.

Implications. The above proposition applies only if the target is higher in a race than in a tournament. But what if the two competitions had the same target ? In that case, tournaments and races have the same marginal type. Therefore, the performance of players in the tournament with reserve are always non-lower than those in the race. This does not imply that it is optimal to set the target. On the contrary, we will show that it is optimal to set an optimal target in a tournament that is below the optimal target in a race. Next section.

3.3 The contest designer's problem

Let us now focus on the contest designer's problem. Imagine the contest designer can choose the competition format ($c = \text{race}, \text{tour}$) to be either the race or the tournament. Let's keep all other aspects of design fixed. The deadline $\bar{t}_c$ is the same between competition formats $\bar{t}_c = \bar{t}$. There is a minimum-entry requirement $\underline{y}_c$ that is higher in the race than in the tournament ($\underline{y}_{\text{race}} > \underline{y}_{\text{tour}}$), where the latter is normalized to zero to ease notation ($\underline{y}_{\text{tour}} = 0$). We will relax this assumption later to consider a more general setting where the level of the minimum-entry requirement is also part of the contest designer's problem.

The contest designer maximizes an objective function that is linearly additive. It consists of the sum of the expected quality achieved by the winners and the corresponding time to completion.

[Question: do the contest designers care about the second place? Assume they don't.]

In a tournament, the objective function is

$$\begin{aligned} R_{\text{tour}} &= \Pr(t_{(1:N)} \leq \bar{t}) \left\{ \int_{a \in \mathcal{A}} y^*(x \mid t_{(1:N)} \leq \bar{t}) dF_{N:N}(x) - \tau \bar{t} - 1 \right\} \\ &= \int y^*(x) dF_{N:N}(x) - \tau \bar{t} - 1. \end{aligned} \tag{20}$$

(recall the prize pool is normalized to one). [Implicitly, you're assuming that the prize is always large enough to ensure positive effort.] [Second prize too is stochastic!!!!]

In a race, the objective function is

$$\begin{aligned} R_{\text{race}} &= \Pr(a_{(N)} \geq \hat{a}) \left\{ \underline{y} - \alpha - \Pr(a_{(N-1)} \geq \hat{a})(1-\alpha) \right\} - \tau \int_{\hat{a}}^{\infty} t^*(x) dF_{N:N}(x) \\ &= [1 - F_{N:N}(\hat{a})] \left\{ \underline{y} - \alpha - [1 - F_{N-1:N}(\hat{a})](1-\alpha) \right\} - \tau \int_{\hat{a}}^{\infty} t^*(x) dF_{N:N}(x). \end{aligned} \tag{21}$$

Note. $t^*(x) \leq \bar{t}$ for all x's. Thus, a lower bound for the above objective function can be computed:

$$\underline{R_{\text{race}}} = [1 - F_{N:N}(\hat{a})] \left\{ \underline{y} - \alpha - [1 - F_{N-1:N}(\hat{a})](1-\alpha) - \tau \bar{t} \right\} \tag{22}$$

An even simpler lower bound is rewriting the above expression as if $\alpha = 1$ (note if the real alpha was set 1 then also mtype would change and therefore setting alpha hits a lower bound only when mtype does xxxx when alpha is 1).

Note. $y^*(x)$ is lower than $\underline{y}$ for all $a < \hat{a}$. Thus, a lower bound of the tournament's expression is

$$\overline{R_{\text{tour}}} = [1 - F_{N:N}(\hat{a})]\underline{y} + \int_{\hat{a}}^{\infty} y^*(x) dF_{N:N}(x) - \tau \bar{t} - 1. \tag{23}$$

Proposition. (a sufficient condition such that) the race "dominates" the tournament is such that $\tau \geq \hat{\tau}$ and otherwise the tournament.

Proof. Simple algebra.

$$\begin{aligned}
\underline{R_{\text{race}}} &\geq \overline{R_{\text{tour}}} \\
[1 - F_{N:N}(\hat{a})](\underline{y} - 1 - \tau\bar{t}) &\geq [1 - F_{N:N}(\hat{a})]\underline{y} + \int_{\hat{a}}^{\infty} y^*(x) dF_{N:N}(x) - \tau\bar{t} - 1 \\
-[1 - F_{N:N}(\hat{a})](\tau\bar{t} + 1) &\geq \int_{\hat{a}}^{\infty} y^*(x) dF_{N:N}(x) - (\tau\bar{t} + 1) \\
F_{N:N}(\hat{a})(\tau\bar{t} + 1) &\geq \int_{\hat{a}}^{\infty} y^*(x) dF_{N:N}(x) \\
\tau &\geq \left[\frac{\int_{\hat{a}}^{\infty} y^*(x) dF_{N:N}(x)}{F_{N:N}(\hat{a})} - 1 \right] \frac{1}{\bar{t}}
\end{aligned} \tag{24}$$

As a result, the intuition was correct. When the preference for time τ is sufficiently high, the race should be preferred. The threshold is a function of the deadline to complete the job (or time horizon). It also depends on the gains in terms of higher performance for all types above the marginal one. The lower the gains, the lower the threshold.

Now we turn to discuss the contest designer's choice of an optimal minimum requirement $\underline{y}$. So far, we have assumed that $\underline{y}_{\text{race}} > \underline{y}_{\text{tour}}$. Now, we show that the assumption that xxxx is indeed an optimal choice of the contest designer. This is summarized in the next proposition.

Proposition. Suppose the contest designer can choose the target that max profits in both the race and the tournament. Then, the optimal $\underline{y}$ in tournament is generally lower than that in a race.

To prove that it is indeed the case. We proceed in two steps. First, we assume that the contest designer does not care about minimizing the timing of the innovation by imposing $\tau = 0$. For simplicity, assume that $\alpha = 1$ (winner-takes-all). In a race, this means that the optimal target will be a value that makes equal the costs in terms of less participation versus the gains in terms of higher values of the winning solutions. Formally, the contest designer's problem in a race is

$$\text{maximize } R^{\text{race}} = [1 - F_{N:N}(\hat{a})](\underline{y}_{\text{race}} - 1). \tag{25}$$

Note that $\hat{a}$ depends on the target. This is clearly concave in $\underline{y}_{\text{race}}$. Thus, the first order condition is also sufficient.

$$\text{FOC } \Rightarrow -F'_{N:N}(\hat{a})\hat{a}'(\underline{y}_{\text{race}} - 1) + [1 - F_{N:N}(\hat{a})] = 0. \tag{26}$$

In a tournament, ...

$$\text{maximize } R^{\text{race}} = \int_{\hat{a}}^{\infty} y^*(x, \underline{y}) dF_{N:N}(x) - [1 - F_{N:N}(\hat{a})]. \tag{27}$$

Convexity is not sure. If not, then the optimal target is zero. Which is lower than the optimal target in a race.

Instead. If the objective function is (strictly) concave then there's an internal solution.

$$\begin{aligned}
\text{FOC } \Rightarrow & \frac{d \int_{\hat{a}}^{\infty} y^*(x, \underline{y}) dF_{N:N}(x))}{d\underline{y}} + F'_{N:N}(\hat{a})\hat{a}' = 0 \\
& \text{(by using Leibniz rule)} \\
\Rightarrow & - y^*(\hat{a}, \underline{y})\hat{a}' F'_{N:N}(\hat{a}) + \int_{\hat{a}}^{\infty} \frac{\partial y^*(x, \underline{y})}{\partial \underline{y}} dF_{N:N}(x) - F'_{N:N}(\hat{a})\hat{a}' = 0 \\
\Rightarrow & - \underline{y}\hat{a}' F'_{N:N}(\hat{a}) + \int_{\hat{a}}^{\infty} \frac{\partial y^*(x, \underline{y})}{\partial \underline{y}} dF_{N:N}(x) - F'_{N:N}(\hat{a})\hat{a}' = 0.
\end{aligned} \tag{28}$$

Using (26) with (28), the optimal target is the same in the race and the tournament only if

$$\int_{\hat{a}}^{\infty} \frac{\partial y^*(x, \underline{y})}{\partial \underline{y}} dF_{N:N}(x) = [1 - F_{N:N}(\hat{a})]. \tag{29}$$

$$\frac{\partial y^*(x, \underline{y})}{\partial \underline{y}} = \frac{c_y'(\underline{y})}{c_y'(y^*(x, \underline{y}))}.$$

Then.

- If $c_y(\cdot)$ is linear, we have that the ratio is one for all x.
- If $c_y(\cdot)$ is convex, then we have that it is less than one. If
- If $c_y(\cdot)$ is concave, then we have that it is higher than one.

As a result, if linear or convex the first order condition is lower than that in the race. Since the obj. function is concave (second order is decreasing), the target should be lower in a tournament than in a race to satisfy the first order condition. (a lower target increases the focs.).

Conjecture. If $\tau > 0$, the $\underline{y}$ in the race is higher.

3.4 Structural econometric model

Readings:

- The winner's curse, reserve prices, and endogenous entry: Empirical insights from eBay auctions
- Entry and competition effects in first-price auctions: theory and evidence from procurement auctions
- Auctions with entry

General two-step strategy:

- First step. Identify the marginal type from the data and the distribution of types.
- Second step. Using the estimated distribution of types.

Basic idea. Equilibrium condition gives:

$$y_i^* = y^*(a_i; F_{\mathcal{A}}). \tag{30}$$

with $y^*(\cdot)$ being an invertible function with ϕ denoting the inverse.
Hence the distribution of bids is

$$F_Y(y) = \Pr(y_i^* \leq y) = \Pr(y^*(a_i) \leq y) = \Pr(a_i \leq \phi(y)) = F_{\mathcal{A}}(\phi(y)). \tag{31}$$

Identification of the model. suggest

4 The experimental design

The field experiment was conducted between March 2 and 16, 2016. The context of the experiment was an online programming contest. In an online programming contest, participants compete to write source code that solves a designated problem. These contests are quite common and xxxx either as a tournament or a race competition.

The contest was hosted on the online platform Topcoder.com. Since its launch in 2001, Topcoder.com administers on a weekly basis several competitive programming contests for thousands of competitors from all over the world. Typical assigned problems are data science problems (e.g., classification, prediction, natural language processing) that demand some background in machine learning and statistics. All Topcoder members (about 1M registered users in 2016) can compete and attain a "rating" that provides a metric of their ability as contestants. Other than attaining a rating, the competitors having made the top five submissions in a competition are typically awarded a monetary prize the extent of which depends on the nature and complexity of the problem but is generally between $5,000 and $20,000.

In this study, we worked together with researchers from the United States National Health Institute (NIH) and the Scripps Research Institute (SCRIPPS) to select a challenging problem for the experimental programming competition. The selected problem was based on an algorithm called BANNER built by NIH (**?**) that uses expert labeling to annotate abstracts from a prominent life sciences and biomedical search engine, PubMed, so disease characteristics can be more easily identified. The goal of the programming competition was to improve upon the current NIH's system by using a combination of expert and non-expert labeling, as described by **?**.

The competition was announced on the platform and to all community members via email. A preliminary online registration was required to enroll in the competition, which resulted in 340 pre-registered participants. Among the pre-registered members, we selected the 299 who had registered to a programming contest at least once before the present contest. This choice was to ensure that participants were xxxx.

Participants were then randomly assigned to separate groups of 10 or 15 people. In each of these groups, contestants were given access to a "virtual room" that is a private web page listing handles of the other participants of the group, a leaderboard updated regularly during the competition, and a common chat that they can use to ask clarifying questions (visible to everyone in the group) with respect to the problem at hand.

A problem statement containing a full description of the algorithmic challenge, the rules of the game, and payoffs was published at the beginning of the submission phase. The submission phase was of 8 days in which participants could submit their computer programs. Each submission was automatically scored and feedback in the form of preliminary scores was published regularly on the website via the leaderboard.

Groups were randomly assigned to one of three different competitive settings: a race, a tournament, and a tournament with a *reserve target*, which is the lowest acceptable score by the platform for a submission to be awarded a prize.

The experimental design is summarized by the Table XXXX.

Table 1: Experimental design

	Large	Small
Race	60	39
Tournament	60	40
Reserve	60	40

In all groups, the first placed competitor was awarded a prize of $1,000, and an additional, consolatory prize of $100 was awarded to the second one.

In a race competition, however, the first to achieve a score equal to xxxx was placed first. The level was chosen xxxx.

In a tournament, xxxx.

Finally, in a tournament with reserve, xxxx.

Additional grand prizes of xxxx were awarded to the top xxx in every treatment.

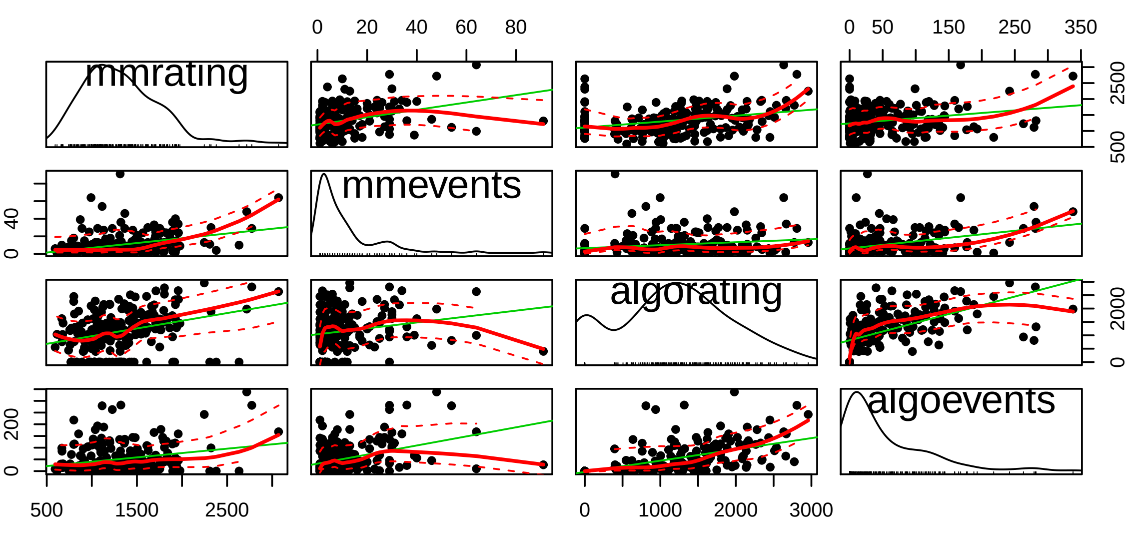
4.1 Data

The bulk of our data comes from the online Topcoder's profile of each participant. This profile typically includes information of when the member registered to the platform, the current rating in a variety of different competitions, the number of past competitions, and so on. Additional demographic information, was collected via a pre-registration survey where competitors were asked to state their gender, age, geographic origin, etc. Participants were als also asked a self-reported measure of risk aversion [xxx] and to forecast how many hours they expected to compete in the next few days of the challenge(the exact question was: "looking ahead xxxx").

Finally, we also asked participants to respond to a survey at the end of the submission phase. In this final survey, they were asked to look back and tell us their best estimate of the time spent working on the problem. Also, we gathered comments on the xxx. And questions such as xxxx.

Table XXX summarizes the data.

A total of 299 competitors signed-up to take part in the challenge. They were all xxxx members of the platform with between 52.5416667 and 770.547619 weeks as registered members. In terms of skill ratings, the distribution was highly skewed with competitors in the highest 90th percentile having participated in 24 more competitions than those in the 10th percentile. Likewise skills as measured by the individual ratings, if there was one, had a skewed distribution with 1034 higher points than those in the 10th percentile; see Figure **??**.



Considerable geographic variation of registered participants.

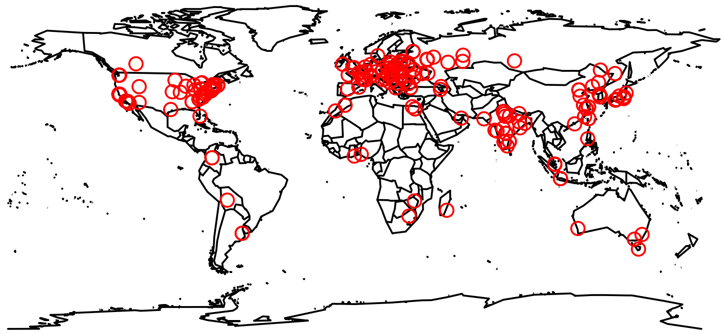
Table 2: Descriptive statistics

Variable	Response Category	Frequency	P-value
country_name	India	36	1.000
	China	31	
	United States	31	
	Japan	27	
	Russia	26	
	(Other)	148	
age	<20 years old	18	0.893
	20-25 years old	99	
	26-30 years	82	
	31-40 years	67	
	41-50 years	21	
	51 years and above	12	
gender	Female	20	0.672
	Male	279	
educ	PhD	31	0.454
	High School	37	
	Master of Arts	111	
	Bachelor	120	
plang	C#	33	0.640
	C++	134	
	Java	87	
	Other	14	
	Python	28	
	VB	3	

Notes: This table shows the frequency for each response category of five categorical variables for country of residence, age, gender, highest degree achieved, and preferred programming language. For each variable, a Pearson's Chi-squared test shows no evidence of dependence between the variable and the treatments. P-values are reported in the last column.

Table 3: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Algo rating	299	1,051.0	730.0	0	2,958
Algo competitions	299	40.6	57.7	0	338
Algo registrations	299	45.7	64.3	0	365
MM rating	205	1,322.0	425.0	593	3,071
MM competitions	299	7.2	11.8	0	91
MM registrations	299	17.6	23.0	1	161
Time zone	299	2.3	5.1	−8.0	10.0
Risk aversion	279	6.4	2.2	1	10



5 Results

In the eight-day submission period, we collected a total of 1759 submissions made by 86 participants. The frequency distribution of submissions was rather skewed with participants in the 90th percentile making 50 more submissions than those in the 10th percentile.

```
##
##          Race Tournament Reserve
##   FALSE    73         67      73
##   TRUE     26         33      27
```

Participation across treatments was higher in the Tournament treatment (33 percent), followed by the Tournament w/reseve (27 percent), and the Race treatment (26.2626263 percent). However, these differences are not statistically significant (using a Fisher's Exact Test for Count Data gives a p-value of 0.5255004)

Figure xxx shows the participation rates by rooms.

```
##
##          Race Tournament Reserve
##   FALSE    84         81      85
##   TRUE     15         19      15
```

Similar results are found when we consider only those who made submissions above a score of xxxx. Participation across treatments was higher in the Tournament treatment (19 percent), followed by the Tournament w/reseve (15 percent), and the Race treatment (15.1515152 percent). However, these differences are not statistically significant (using a Fisher's Exact Test for Count Data gives a p-value of 0.6991539)

```
##        Race Tournament    Reserve
##          12          6         15
```

Regarding to the frequency of submissions per participant, the median count is larger in the race and in the tournament w/reserve (12 and 15 respectively) compared to the Tournament (a median of 6 submissions). However, a Kruskal-Wallis rank sum test fails to reject the null hypothesis (p=0.7935069) that at least one treatment was different in the location of the frequency distribution of the submissions.

```
##        Race Tournament    Reserve
##       0.799      0.805      0.808
```

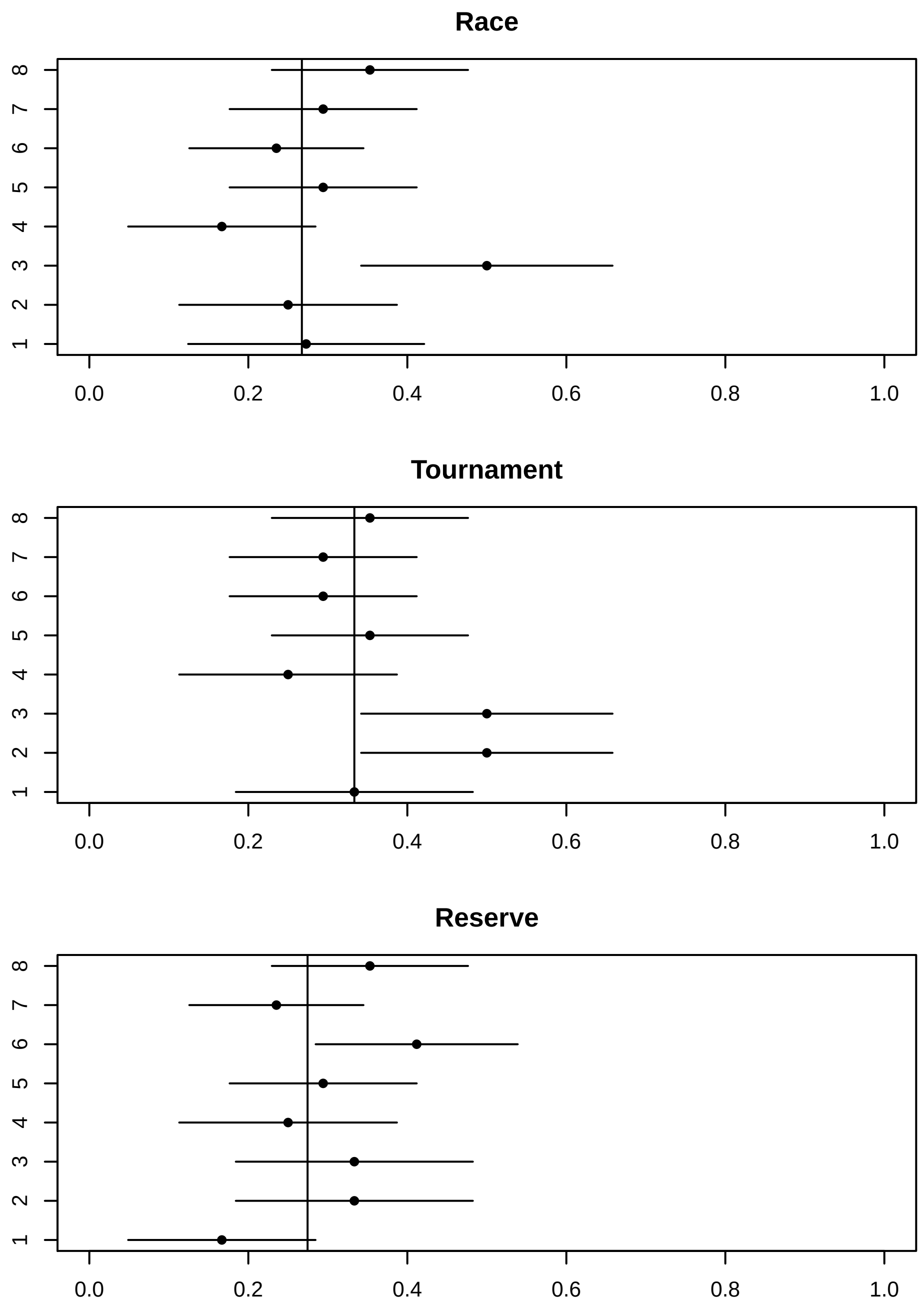


Figure 1: Participation rates by rooms

Concerning the distribution of the scores on the last submission, the median final scores was higher in the Tournament w/reserve treatment (0.8084504), followed by the Tournament (0.8054121), and the Race treatment (0.7993725). As before, however, these differences are not statistically significant (a Kruskal-Wallis rank sum test gives a p-value of 0.5768076).

Finally, let us focus on the timing of the first and last submission. xxxx

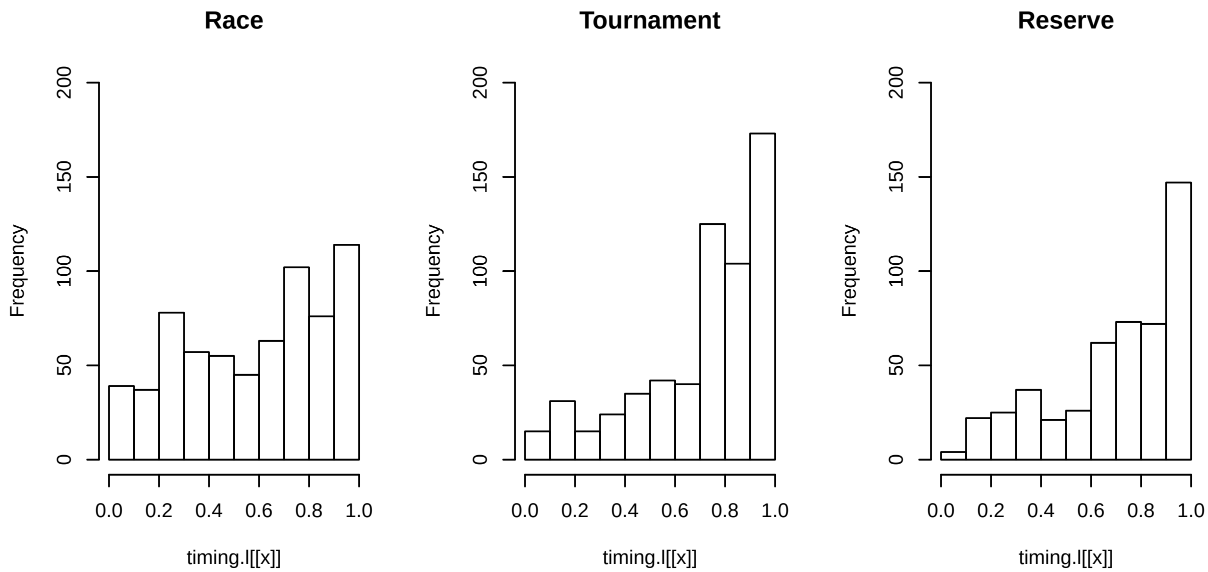


Figure 2: Submissions timing within the submission period

Here we consider the hours of the day on the 24h. We normalize the 24h on the unit interval (here I think we should take into account the different timezoes.)

5.1 Regressions

Although we do not find significant differences through an univariate analysis, it is possible that differences will be xxx in a multivariate analysis. Adding controls can indeed reduce noise and improve precisions of our estimates.

Let's consider first a simple logistic model

```
##
## Call:
## glm(formula = submit ~ treatment, family = quasibinomial, data = races)
##
## Deviance Residuals:
```

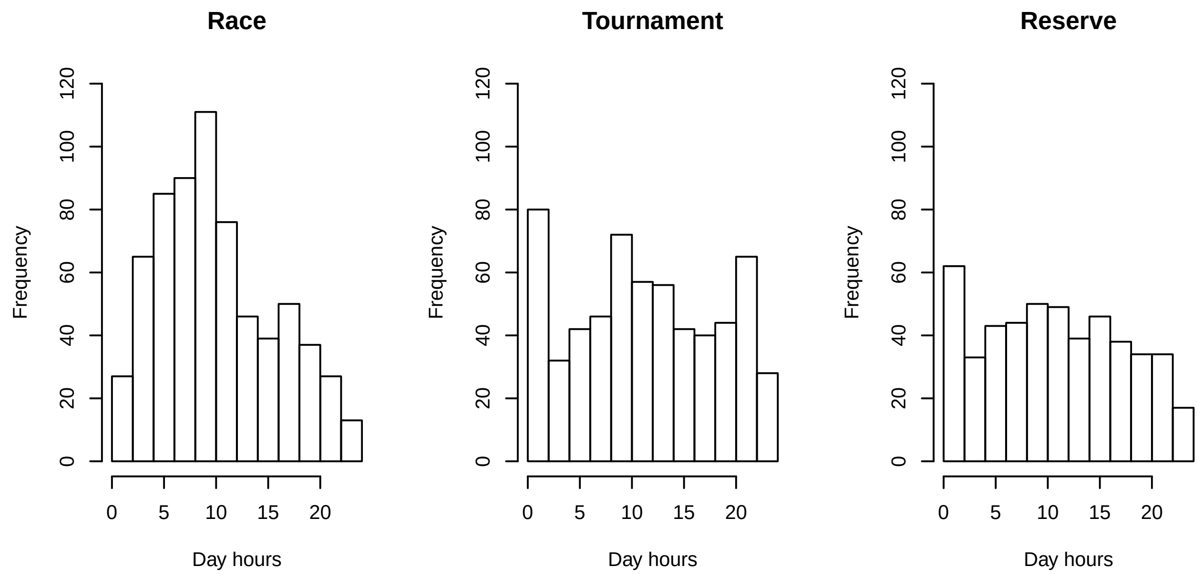


Figure 3: Submissions within the 24h (need to adjust for timezone)

```
##    Min      1Q  Median      3Q     Max
## -0.895  -0.793  -0.781   1.489   1.635
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          -1.0324     0.2295   -4.50  9.9e-06
## treatmentTournament   0.3242     0.3136    1.03     0.30
## treatmentReserve      0.0377     0.3224    0.12     0.91
##
## (Dispersion parameter for quasibinomial family taken to be 1.01)
##
##     Null deviance: 358.81  on 298  degrees of freedom
## Residual deviance: 357.49  on 296  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 4

##
## Call:
## glm(formula = submit ~ treatment + gender + educ + age + timezone +
##     plang, family = quasibinomial, data = races)
```

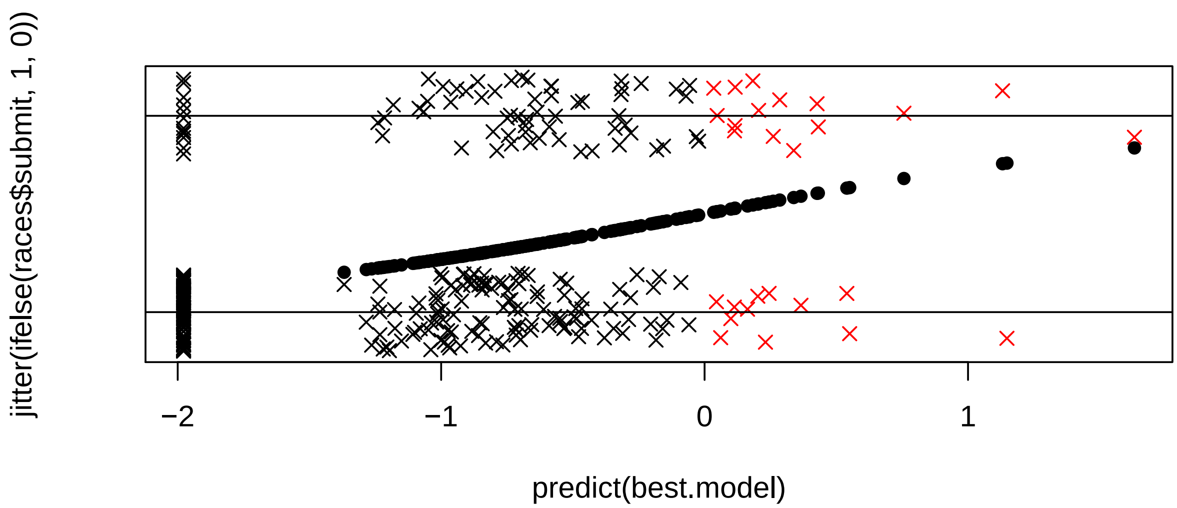
```
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.533  -0.840  -0.648   1.168   2.079
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)            -1.8533     0.9969   -1.86    0.064
## treatmentTournament     0.2977     0.3381    0.88    0.379
## treatmentReserve        0.0454     0.3491    0.13    0.897
## genderMale              0.3312     0.6178    0.54    0.592
## educHigh School         0.8063     0.6322    1.28    0.203
## educMaster of Arts      0.2427     0.4906    0.49    0.621
## educBachelor            0.5050     0.5141    0.98    0.327
## age20-25 years old     -0.3094     0.6757   -0.46    0.647
## age26-30 years          0.5366     0.7060    0.76    0.448
## age31-40 years          0.9886     0.7021    1.41    0.160
## age41-50 years          0.4718     0.8314    0.57    0.571
## age51 years and above   1.1899     0.9109    1.31    0.193
## timezone                0.0109     0.0279    0.39    0.695
## plangC++               -0.1932     0.4441   -0.44    0.664
## plangJava              -0.8340     0.4754   -1.75    0.080
## plangOther             -0.4482     0.7454   -0.60    0.548
## plangPython             0.2196     0.5838    0.38    0.707
## plangVB                 1.1734     1.3532    0.87    0.387
##
## (Dispersion parameter for quasibinomial family taken to be 1.06)
##
##     Null deviance: 358.81  on 298  degrees of freedom
## Residual deviance: 337.25  on 281  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 4

##
## Call:
## glm(formula = submit ~ treatment + algorating + mmevents + algoevents +
```

```
##     totalpayments, family = quasibinomial, data = races)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.713  -0.771  -0.644   1.040   1.908
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               -1.503410   0.327239   -4.59  6.5e-06
## treatmentTournament        0.372238   0.331949    1.12   0.2631
## treatmentReserve          -0.000123   0.343707    0.00   0.9997
## algorating                -0.000059   0.000228   -0.26   0.7957
## mmevents                   0.035712   0.013466    2.65   0.0084
## algoevents                 0.001907   0.003090    0.62   0.5377
## totalpayments1 - 599      -0.182154   0.477411   -0.38   0.7031
## totalpayments600 - 4500    0.226796   0.456516    0.50   0.6197
## totalpayments4500 - 37000  0.723311   0.426958    1.69   0.0913
## totalpayments>37000        0.466569   0.452361    1.03   0.3032
##
## (Dispersion parameter for quasibinomial family taken to be 1.03)
##
##     Null deviance: 358.81  on 298  degrees of freedom
## Residual deviance: 334.04  on 289  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 4

##
## Call:
## glm(formula = submit ~ treatment + algorating + mmevents + algoevents +
##     totalpayments + gender + educ + age + timezone + plang, family = qua
##     data = races)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.966  -0.759  -0.597   0.992   2.211
##
```

```
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               -2.13e+00   1.07e+00   -1.99    0.047
## treatmentTournament        3.50e-01   3.56e-01    0.98    0.327
## treatmentReserve          -5.13e-03   3.70e-01   -0.01    0.989
## algorating                -3.52e-05   2.62e-04   -0.13    0.893
## mmevents                   3.50e-02   1.61e-02    2.17    0.031
## algoevents                 1.65e-03   3.34e-03    0.50    0.621
## totalpayments1 - 599      -2.12e-02   5.18e-01   -0.04    0.967
## totalpayments600 - 4500    2.56e-01   5.07e-01    0.50    0.614
## totalpayments4500 - 37000  7.25e-01   4.68e-01    1.55    0.123
## totalpayments>37000        3.60e-01   5.11e-01    0.70    0.482
## genderMale                 2.56e-01   6.51e-01    0.39    0.694
## educHigh School            8.29e-01   6.66e-01    1.24    0.215
## educMaster of Arts         1.39e-01   5.17e-01    0.27    0.788
## educBachelor               4.14e-01   5.43e-01    0.76    0.446
## age20-25 years old        -2.84e-01   7.17e-01   -0.40    0.692
## age26-30 years             3.45e-01   7.61e-01    0.45    0.651
## age31-40 years             6.57e-01   7.65e-01    0.86    0.391
## age41-50 years            -2.77e-01   9.49e-01   -0.29    0.770
## age51 years and above      5.57e-01   1.02e+00    0.55    0.584
## timezone                   1.17e-02   3.03e-02    0.39    0.700
## plangC++                  -4.17e-02   4.72e-01   -0.09    0.930
## plangJava                 -6.66e-01   4.99e-01   -1.34    0.183
## plangOther                -2.35e-03   7.83e-01    0.00    0.998
## plangPython                3.38e-01   6.13e-01    0.55    0.582
## plangVB                    7.60e-01   1.51e+00    0.50    0.615
##
## (Dispersion parameter for quasibinomial family taken to be 1.09)
##
##     Null deviance: 358.81  on 298  degrees of freedom
## Residual deviance: 320.83  on 274  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 4

##
```

```
## =======================================================
##                           Dependent variable:
##                     ---------------------------
##                               submit
##                          (1)            (2)
## -------------------------------------------------------
## poly(mmevents, deg = 3)1   12.200***
##                           (4.120)
##
## poly(mmevents, deg = 3)2     1.210
##                           (6.130)
##
## poly(mmevents, deg = 3)3     8.110*
##                           (4.740)
##
## poly(mmevents, deg = 2)1                   4.690*
##                                           (2.540)
##
## poly(mmevents, deg = 2)2                  -0.212
##                                           (2.470)
##
## poly(mmrating, deg = 2)1                 10.100***
##                                           (3.120)
##
## poly(mmrating, deg = 2)2                  -0.942
##                                           (2.380)
##
## Constant                  -0.961***      -1.020***
##                           (0.138)        (0.143)
##
## -------------------------------------------------------
## Observations                 299            299
## Log Likelihood            -166.000       -164.000
## Akaike Inf. Crit.          341.000        337.000
## =======================================================
## Note:                    *p<0.1; **p<0.05; ***p<0.01
```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: submit
##
## Terms added sequentially (first to last)
##
##
##                             Df Deviance Resid. Df Resid. Dev Pr(>Chi)
## NULL                                          298        359
## poly(mmevents, deg = 2)  2     20.4       296        338  3.7e-05
## poly(mmrating, deg = 2)  2     11.1       294        327   0.0039
```



This result does not seem to correlate well with the competitor's experience or skills, as the Pearsons's correlation coefficient between the count of past competitions or the rating and the count of submissions is positive but generally low; see Table XXX. Thus, differences in submissions appear idiosyncratic and perhaps related to the way to organize the work rather than systematically associated with underlying differences in experience or skills.

The timing of submissions was rather uniform during the submission period with a peak of submissions made in the last of the competition. (explain more)

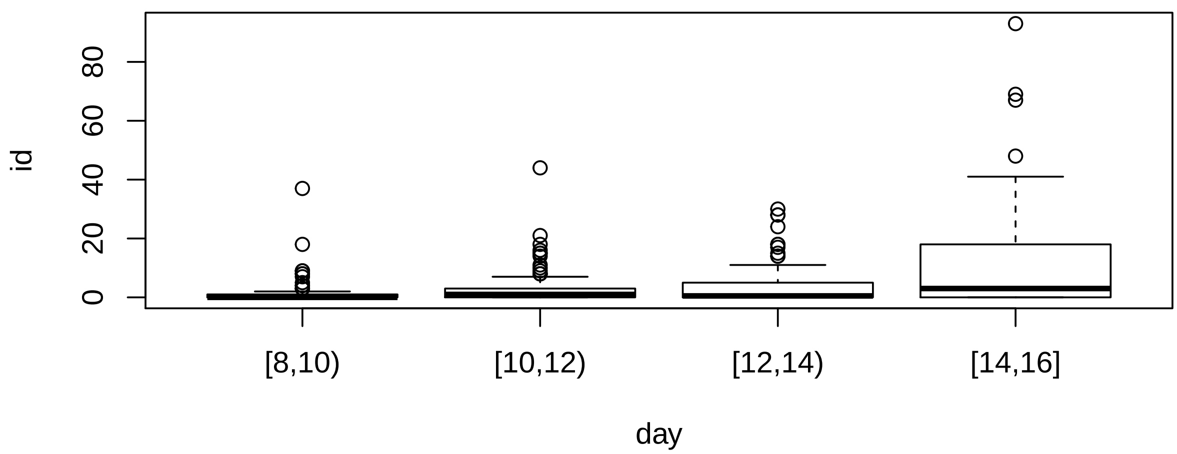
```
#scores$submax <- ave(races.sub$id, races.sub$handle, FUN=max)
```

```
#par(mfrow=c(2, 1), mar=c(4,4,2,2))
#plot(subid==1 ~ as.POSIXct(subts), data=scores, type='h', yaxt='n'
#    , xlab='', ylab='', main='Dispersion time first submission')
#plot(subid==submax ~ as.POSIXct(subts), data=scores, type='h'
#    , yaxt='n', xlab='', ylab='', main='Dispersion time last submission')
```

Proportions by rooms.

```
nsub <- tapply(races.sub$id, races.sub$handle, length)
races$submit <- races$handle %in% names(nsub)
treat <- tapply(races$treatment, races$room, unique)
n1 <- tapply(races$submit, races$room, sum)
n <- tapply(races$submit, races$room, length)
p <- (n1 + 1) / (n + 2)
SE <- sqrt(p*(1-p) / (n+2))
CI <- cbind(p+1.96*SE, p - 1.96*SE)

# All rooms
plot(p, 1:length(p), xlim=c(-0.1, 1), yaxt='n', bty='n', ann=FALSE, col=trea
segments(y0=1:length(p), x0=p+SE, x1=p-SE, col=treat, lwd=3)
segments(y0=1:length(p), x0=CI[, 1], x1=CI[, 2], col=treat)
text(y=1:length(p), x=p, levels(races$treatment)[treat], pos=3, cex=0.5, xpo
abline(v=mean(races$submit))

# Large rooms
treat <- treat[n<15]
p <- p[n<15]
n <- n[n<15]
SE <- sqrt(p*(1-p) / (n+2))
CI <- cbind(p+1.96*SE, p - 1.96*SE)
plot(p, 1:length(p), xlim=c(-0.1, 1), yaxt='n', bty='n', ann=FALSE, col=trea
segments(y0=1:length(p), x0=p+SE, x1=p-SE, col=treat, lwd=3)
segments(y0=1:length(p), x0=CI[, 1], x1=CI[, 2], col=treat)
text(y=1:length(p), x=p, levels(races$treatment)[treat], pos=3, cex=0.5, xpo
abline(v=mean(races$submit))
```

Consider panel data!




```
##
## Call:
## glm(formula = id ~ day, data = subs.long)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -11.69   -4.00   -1.59    0.08   81.31
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)     1.59       1.08    1.47     0.14
## day[10,12)      1.58       1.53    1.03     0.30
## day[12,14)      2.41       1.53    1.57     0.12
## day[14,16]     10.09       1.53    6.60  1.6e-10
##
## (Dispersion parameter for gaussian family taken to be 101)
##
##     Null deviance: 39401  on 343  degrees of freedom
## Residual deviance: 34190  on 340  degrees of freedom
## AIC: 2568
##
## Number of Fisher Scoring iterations: 2
```

```
##
## Call:
## glm(formula = id ~ day, family = quasipoisson, data = subs.long)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -4.834  -2.828  -1.785   0.023  14.939
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.466      0.342    1.36    0.174
## day[10,12)     0.689      0.419    1.65    0.101
## day[12,14)     0.921      0.404    2.28    0.023
## day[14,16]     1.993      0.365    5.47  8.9e-08
##
## (Dispersion parameter for quasipoisson family taken to be 16)
##
##     Null deviance: 4500.3  on 343  degrees of freedom
## Residual deviance: 3587.7  on 340  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 6
```

```
##
## Call:
## glm(formula = id > 0 ~ day, data = subs.long)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -0.733  -0.500   0.267   0.465   0.651
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.3488     0.0521    6.70  8.7e-11
## day[10,12)    0.1860     0.0736    2.53    0.012
## day[12,14)    0.1512     0.0736    2.05    0.041
## day[14,16]    0.3837     0.0736    5.21  3.3e-07
```

```
##
## (Dispersion parameter for gaussian family taken to be 0.233)
##
##     Null deviance: 85.709  on 343  degrees of freedom
## Residual deviance: 79.279  on 340  degrees of freedom
## AIC: 481.4
##
## Number of Fisher Scoring iterations: 2
```

Scores: xxxx

5.2 Treatment differences

Difference in participation by treatments are show in Table XX.

```
Fisher's Exact Test for Count Data
```

data: tab p-value = 0.5 alternative hypothesis: two.sided

We find no differences in the room size.

```
Fisher's Exact Test for Count Data
```

data: tab p-value = 1 alternative hypothesis: true odds ratio is not equal to 1 95 percent confidence interval: 0.569 1.691 sample estimates: odds ratio 0.985

Ex-post

Timing: early vs late

Using a Chi-square test of independence, we find no significant differences in participation rates associated with the assigned treatments (p-value: 1); see Table XX.

Further, we model participation rates as a logistic regression. We use a polynomial of third degree for the count of past competitions to account for non-linear effects of experience; and we use an indicator for whether the competitor had a win or not. Also, taking into account differences in ability, participation rates are not significantly different.

5.3 Estimation results

Participation to the competition by treatment is shown in Figure **??**. Participation here is measured by the proportion of registered participants per treatment who made any submission during the eight-day submission period. Recall that competitors may decide to enter into the competition and work on the problem without necessarily submitting. In a tournament, for example, competitors are awarded a prize based on their last submission and may decide to drop out without submitting anything. However, this scenario seems unlikely. In fact, competitors often end up making multiple submissions because by doing so they obtain intermediate feedback via preliminary scoring (see Section XXX for details). In a race, competitors have even stronger incentives to make early submissions as any submission that hits the target first wins.

`Table xxx`

We find that the propensity to make a submission is higher in the Tournament than in the Race and in the Tournament with reserve, but the difference is not statistically significant (a Fisher's exact test gives a p-value of xxxxx). As discussed in Section XXX, we may not have enough power to detect differences below 5 percentage points. However, we find the same not-significant result in a parametric regression analysis of treatment differences with controls for the demographics and past experience on the platform; see Table **??**. Adding individual covariates reduces variability of outcomes, potentially increasing the power of our test. In particular, Table **??** reports the results from a logistic regression on the probability of making a submissions. Column 1 reports the results from a baseline model with only treatment dummies. Column 2 adds demographics controls, such as the age, education, and gender. Column 3 adds controls for the past experience on the platform. Across all these specifications, the impact of the treatment dummies (including room size) on entry is not statistically significant.

5.4 Simulation results

6 Empirical analysis

6.1 Estimation results

Participation to the competition by treatment is shown in Figure

$$fig : entry$$

. Participation here is measured by the proportion of registered participants per treatment who made any submission during the eight-day submission period. Recall that competitors may decide to enter into the competition and work on the problem without necessarily submitting. In a tournament, for example, competitors are awarded a prize based on their last submission and may decide to drop out without submitting anything. However, this scenario seems unlikely. In fact, competitors often end up making multiple submissions because by doing so they obtain intermediate feedback via preliminary scoring (see Section XXX for details). In a race, competitors have even stronger incentives to make early submissions as any submission that hits the target first wins.

`Table xxx`

We find that the propensity to make a submission is higher in the Tournament than in the Race and in the Tournament with reserve, but the difference is not statistically significant (a Fisher's exact test gives a p-value of xxxx). As discussed in Section XXX, we may not have enough power to detect differences below 5 percentage points. However, we find the same not-significant result in a parametric regression analysis of treatment differences with controls for the demographics and past experience on the platform; see Table

$$entry$$

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$$entry$$

reports the results from a logistic regression on the probability of making a submissions. Column 1 reports the results from a baseline model with only treatment dummies. Column 2 adds demographics controls, such as the age, education, and gender. Column 3 adds controls for the past experience on the platform. Across all these specifications, the impact of the treatment dummies (including room size) on entry is not statistically significant.

6.2 Simulation results