Races or Tournaments? [PRELIMINARY AND INCOMPLETE]*

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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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Contents

1 Introduction

A contest is a competition where participants attempt to win a prize by investing time and energy in a project. A typical goal for contest designers is to maximize competitors efforts while minimizing the time to complete the project. Balancing between these two desirable but often incompatible goals is often difficult. When contest designers lack full knowledge of individual costs and skills, design choices are made under considerable uncertainty. A large economic literature on contest design offers insights on how to make better resolutions. However, how to achieve an optimal design is still a largely open question.

We investigate one key aspect of contest design which is the way people compete. In particular, we contrast two forms of competition with one another; the "race," where the first to finish an innovation project wins; and the "tournament," where the best finished project wins.

One is xxx the other is xxxx. To fix ideas about this trade-off, imagine a government tasked with the design of an innovation contest to progress on finding a solution to a problem of public health, such as the problem of antibiotic resistance.[1] To minimize the risks that the threat of xxxx will materialize before a solution is found, one choice is to design the contest as a tournament competition with a tight deadline for participants to provide their solutions. However, if the duration of the competition is too low, a tournament may give insufficient incentives resulting in inadequate solutions. Alternatively, the government can set up a race competition with a prize being awarded to the first competitor who achieves, or goes beyond, a minimum quality threshold. Here the problem of accelarating the timing of innovation should not be a big issue but competitors may work inefficiently, as they have no incentives to exceed the minimum threshold. Clearly, fixed the prize structure, both approaches have specific advantages and limitations. However, xxxx.

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 Moldovanu and Sela (2001). 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 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

[1] This example is taken...

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 (Leaman et al., 2008) 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 Good et al. (2014). 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 Dixit (1987) Baye and Hoppe (2003), Parreiras and Rubinchik (2010), Moldovanu and Sela (2001), Moldovanu and Sela (2006), Siegel (2009), Siegel (2014). It also relates to the literature on innovation contests Taylor (1995), Che and Gale (2003). And the personnel economics approach to contests Lazear and Rosen (1981), Green and Stokey (1983), Mary et al. (1984).

Empirically, Dechenaux et al. (2014) provide a comprehensive summary of the experimental literature on contests and tourments. Large body of empirical works have focused on sports contests Szymanski (2003). More recently, inside firms (xxx) and online contest (xxxx).

This paper is also related to the econometrics of auctions Paarsch (1992), Laffont et al. (1995), Donald and Paarsch (1996) and more recently Athey et al. (2011), Athey and Haile (2002), and Athey and Haile (2007).

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.

Harris and Vickers (1987), Grossman and Shapiro (1987) investigate the dynamics issues patent races where the interest is how firms compete for a patent. Bimpikis et al. (2014) 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, Zizzo (2002) 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 Baye and Hoppe (2003), 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

We now generalize the contest game introduced by Moldovanu and Sela (2001) to a situation where players simultaneously decide i) the quality and ii) how fast to produce a given output. Then we explore the problem of revenue 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 in which each player ($i = 1, ..., n$) competes against the others to win a prize. Players assign a nonnegative value v_k to each prize ($k = 1, ..., q$) that is decreasing in the prize rank ($v_1 \geq v_2 \geq ... \geq v_q$). Each player's strategy consists in choosing an output quality y_i and a timing t_i both nonnegative numbers that determine player i's probability $p_k(y_i, t_i)$ of winning a prize k.

Each player incurs a production cost c_i that is shaped by a cost function $C(\cdot)$ which is increasing in quality and decreasing in timing. The cost function also depends on an individual ability parameter a_i that is private information of each player and that is drawn at random from a common distribution F on a finite interval $[\underline{a}, \bar{a}]$ with $\underline{a} > 0$.[2] For simplicity, we assume the cost function is multiplicative:

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

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 impose additional conditions to ensure nonnegative costs

$$c_a(\bar{a}) > 0, c_t(\underline{a}) > 0, \text{ and } c_y(\underline{a}) \geq 0.$$

Player i's payoff is then

$$\pi_i = \sum_{k=1}^{q} p_k(y_i, t_i)v_k - C(a_i, y_i, t_i). \tag{2}$$

And we can denote a (generalized) contest game G by

$$G \equiv \{n, q, \{v_k\}_{k=1}^{q}, F, C, \{p_k\}_{k=1}^{q}\}. \tag{3}$$

When players have to successfully meet a given deadline and/or satisfy a minimum quality level to be eligible to win a prize, we say that the contest game G has a minimum-entry requirement. Let $\bar{t} > 0$ be the deadline and $\underline{y} \geq 0$ the required minimum performance. A game G has a minimum-entry requirement when, for every prize k and player i, the probability $p_k(\cdot, \cdot) = 0$ when player i's quality is below a target level $q_i < \underline{y}$ or the timing to completion is above a given deadline $t_i > \bar{t}$. To simplify exposition, we further use the convention that whenever the deadline is not met $t_i > \bar{t}$ then the output quality is zero $y_i = 0$, and whenever the required quality is not met $y_i < \underline{y}$ then

[2] This assumption rules out common parametric distributions like the log-normal and forces us to focus the analysis on beta-type distributions. However, results do not hinge on this particular assumption.

the time of completion is above the deadline $t_i = \infty$. This simply ensures that when one of the entry-requirements is not met by a player, the player has a zero probability of winning a prize.

Using the above notation, we define a tournament as a contest game with the following characteristics.

Definition 1 (Tournament)**.** Let $y_{(1:n-1)}, ..., y_{(n-1:n-1)}$ denote the order statistics of the y's for the $n-1$ opponents of player i. A tournament is a contest game G with a minimum-entry requirement $\bar{t} > 0$ where player i's probability of winning a prize is zero when $t_i > \bar{t}$. Otherwise, when $t_i \leq \bar{t}$, the probability is

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

In other words, the tournament corresponds to a special case of a contest game with minimum-entry requirement 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.

In a similar way, we describe a race as a contest game with the following characteristics.

Definition 2 (Race)**.** Let $t_{(1:n-1)}, ..., t_{(n-1:n-1)}$ denote the order statistics of the t's for the $n-1$ opponents of player i. A race is a contest game G with a minimum-entry requirement $\underline{y} > 0$ where player i's probability of winning a prize is zero if $y_i < \underline{y}$. Otherwise, when $y_i \geq \underline{y}$, the probability is

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

That is, 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.

3.2 Equilibrium

In this section, we solve the model for the equilibrium actions of players. We assume throughout that there are only two prizes of total value normalized to one, where the fraction $\alpha \geq 1/2$ goes to the first placed competitor and $1-\alpha$ goes to the second placed competitor. We also let $F_{r:n}$ and $f_{r:n}$ be the distribution and density function of the r^{th} order statistic (i.e., the r^{th} lowest realization) of n draws from the ability distribution (i.e., the a's).

3.2.1 Equilibrium in a tournament

Because the probability of winning a prize in a tournament is not affected by the completion time (as soon as the deadline is met), picking a completion time equal to the deadline ($t_i = \bar{t}$) is a (weakly) dominant strategy for each player. Hence, from the point of view of the contest designer, imposing a more distant deadline has the same effect as a reduction in the marginal costs for everyone (i.e., proportional to the cost $c_t(\bar{t})$). [Alternatively, it can be seen as a reduction in the total value of prizes.]

Following Moldovanu and Sela (2001), the (unique) symmetric equilibrium for each player i is the timing $t_i^* = \bar{t}$ and the output quality $y_i^* = y^*(a_i)$ with the function

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

where

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

and

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

An important property of (6) is that it has its upper bound in XXXX and lower bound in $y^*(\underline{a}) = 0$. Also, equilibrium output quality is monotonic increasing in the agent's ability (see Moldovanu and Sela, 2001). Thus, using ϕ to denote the inverse function, the above equilibrium strategy is obtained by solving the first-order differential equation:

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

with boundary condition $\phi(0) = \underline{a}$ (i.e., the lowest-ability competitor's optimal output quality is zero).

Also, monotonicity of the equilibrium output quality implies that, for every $i = 1, ..., n$, the equilibrium expected payoff from the contest π_i^* depends on the rank of the player's ability relative to the others. That is, the equilibrium payoff is $\pi_i^* = \pi^*(a_i)$ with

$$\pi^*(a_i) = \alpha F_{n:n}(a_i) + (1-\alpha)[1 - F_{n:n}(a_i)] F_{n-1:n-1}(a_i) - C(y^*(a_i), \bar{t}, a_i), \tag{10}$$

where $\pi^*(0) = 0$ and $\pi^*(\bar{a}) = \alpha - C(y^*(\bar{a}), \bar{t}, \bar{a}) > 0$.

3.2.2 Equilibrium in a race

In a similar way, one can derive the equilibrium strategy in a race. Because any quality that is below the minimum-entry requirement $\underline{y}$ will give a zero probability of winning and any quality that is above $\underline{y}$ is costly but gives a constant probability of winning, player i's choice of optimal quality y^* is either zero (with $t_i = \bar{t}$ by convention) or $y^* = \underline{y}$.

The (unique) symmetric equilibrium for player i is the xxxxx when $xxxx$ and xxxx.

$$t^* = XXXX \tag{11}$$

where

$$A(x) = XXXX \tag{12}$$

and

$$B(x) = XXXX. \tag{13}$$

An important property of XX is that $y^*(a_i)$ has its upper bound in XX and lower bound in XX. Also, equilibrium output quality is monotonic increasing in the agent's ability (see Moldovanu and Sela, 2001). 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

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

$$\underline{a} = h(n, V, F_A, C, d). \tag{14}$$

3.2.3 Tournament vs races

By comparing equilibrium xxx and xxx, we find that the race and the tournament do not (ex-post) dominate one another with respect to output quality. Whereas the race always dominates the tournament with respect to completion time. [This is only when the deadline is the same. Otherwise, there's always xxxx.] This result is stated below.

Proposition 1. *There always exist an interval of abilities where the output quality is higher in the race than in the tournament. By contrast, every player takes less completion time in the race 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.

```
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 to be either the race or the tournament. Imagine all other aspects of design are given. The prize structure α has been already chosen. There is a deadline $\bar{t}$, which is the same in both competition formats. [The quality requirement $\underline{y}_c$ in the tournament is smalle than that in the race $\underline{y}_{\text{race}} > \underline{y}_{\text{tour}}$)] We will relax this assumption later to consider a more general setting where these variables are also part of the contest designer's problem.

The contest designer has an objective function that is increasing in the expected quality of the winning solution and decreasing in the corresponding time to completion. Here, to do not complicate exposition, we assume that the contest designer cares about the winning submission only: second placed efforts are not considered. [If the principal values the diversity of the solutions … but we assume it does not.]

XXX EQUATION XXXX

The optimal choice involves a comparison of the expected profits between the race and the tournament. Given xxxx, we can show that there will be a threshold on the cost of completion time $\hat{\tau}$ above which the race is a better choice than the tournament, and vice versa.

Proposition 2. *There's a tau above which ...*

Proof. In a tournament, the objective function is

$$
\begin{aligned}
R_{\text{tour}} &= \Pr(t_{(1:n)} \leq \bar{t}) \left\{ \int y^*(x \mid t_{(1:n)} \leq \bar{t}) dF_{n:n}(x) - \tau \bar{t} - 1 \right\} \\
&= \int_{\hat{a}}^{\bar{a}} y^*(x) dF_{n:n}(x) - \tau \bar{t} - 1. \qquad (15)
\end{aligned}
$$

That is, the contest designer's objective function is the sum of the expected output quality for a given deadline, minus the cost τ of having the winner working on the task until completion (i.e., until the deadline), and the cost of the prize pool (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

$$
\begin{aligned}
R_{\text{race}} &= \Pr(a_{(N)} \geq \hat{a}) \left\{ \underline{y} - \alpha - \Pr(a_{(N-1)} \geq \hat{a})(1-\alpha) \right\} - \tau \int_{\hat{a}}^{\infty} t^*(x) dF_{N:N}(x) \\
&= [1 - F_{N:N}(\hat{a})] \left\{ \underline{y} - \alpha - [1 - F_{N-1:N}(\hat{a})](1-\alpha) \right\} - \tau \int_{\hat{a}}^{\infty} t^*(x) dF_{N:N}(x). \qquad (16)
\end{aligned}
$$

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

$$
\underline{R_{\text{race}}} = [1 - F_{N:N}(\hat{a})] \left\{ \underline{y} - \alpha - [1 - F_{N-1:N}(\hat{a})](1-\alpha) - \tau \bar{t} \right\} \qquad (17)
$$

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

$$\overline{R_{\text{tour}}} = [1 - F_{N:N}(\hat{a})]\underline{y} + \int_{\hat{a}}^{\infty} y^*(x)dF_{N:N}(x) - \tau\bar{t} - 1. \tag{18}$$

$$\begin{aligned}
\underline{R_{\text{race}}} &\geq \overline{R_{\text{tour}}} \\
[1 - F_{N:N}(\hat{a})](\underline{y} - 1 - \tau\bar{t}) &\geq [1 - F_{N:N}(\hat{a})]\underline{y} + \int_{\hat{a}}^{\infty} y^*(x)dF_{N:N}(x) - \tau\bar{t} - 1 \\
-[1 - F_{N:N}(\hat{a})](\tau\bar{t} + 1) &\geq \int_{\hat{a}}^{\infty} y^*(x)dF_{N:N}(x) - (\tau\bar{t} + 1) \\
F_{N:N}(\hat{a})(\tau\bar{t} + 1) &\geq \int_{\hat{a}}^{\infty} y^*(x)dF_{N:N}(x) \\
\tau &\geq \left[\frac{\int_{\hat{a}}^{\infty} y^*(x)dF_{N:N}(x)}{F_{N:N}(\hat{a})} - 1\right]\frac{1}{\bar{t}}
\end{aligned} \tag{19}$$

End proof.

When the cost of time τ is sufficiently high, the race is preferred. Interestingly, the threshold is a function of the deadline to complete the job, as xxx. It also depends on the shape of xxxx.

3.3.1 Optimal minimum-entry

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 3. *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

$$\text{maximize } R^{\text{race}} = [1 - F_{N:N}(\hat{a})](\underline{y}_{\text{race}} - 1). \tag{20}$$

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.

$$\text{FOC } \Rightarrow -F'_{N:N}(\hat{a})\hat{a}'(\underline{y}_{\text{race}}-1)+[1-F_{N:N}(\hat{a})]=0. \tag{21}$$

In a tournament, ...

$$\text{maximize } R^{\text{race}}=\int_{\hat{a}}^{\infty} y^*(x,\underline{y})dF_{N:N}(x)-[1-F_{N:N}(\hat{a})]. \tag{22}$$

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.

$$\begin{aligned}
\text{FOC } &\Rightarrow \frac{d\int_{\hat{a}}^{\infty} y^*(x,\underline{y})dF_{N:N}(x))}{d\underline{y}}+F'_{N:N}(\hat{a})\hat{a}'=0\\
&\text{(by using Leibniz rule)}\\
&\Rightarrow -y^*(\hat{a},\underline{y})\hat{a}'F'_{N:N}(\hat{a})+\int_{\hat{a}}^{\infty}\frac{\partial y^*(x,\underline{y})}{\partial \underline{y}}dF_{N:N}(x)-F'_{N:N}(\hat{a})\hat{a}'=0\\
&\Rightarrow -\underline{y}\hat{a}'F'_{N:N}(\hat{a})+\int_{\hat{a}}^{\infty}\frac{\partial y^*(x,\underline{y})}{\partial \underline{y}}dF_{N:N}(x)-F'_{N:N}(\hat{a})\hat{a}'=0.
\end{aligned} \tag{23}$$

Using (21) with (23), the optimal target is the same in the race and the tournament only if

$$\int_{\hat{a}}^{\infty}\frac{\partial y^*(x,\underline{y})}{\partial \underline{y}}dF_{N:N}(x)=[1-F_{N:N}(\hat{a})]. \tag{24}$$

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

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:

$$y_i^* = y^*(a_i; F_{\mathcal{A}}). \tag{25}$$

with $y^*(\cdot)$ being an invertible function with ϕ denoting the inverse.

Hence the distribution of bids is

$$F_Y(y) = \Pr(y_i^* \leq y) = \Pr(y^*(a_i) \leq y) = \Pr(a_i \leq \phi(y)) = F_{\mathcal{A}}(\phi(y)). \tag{26}$$

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 (Leaman et al., 2008) 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 Good et al. (2014).

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.

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.

Table 1: Experimental design

	1	2	3	4	5	6	7	8
Race	9	10	10	10	15	15	15	15
Tournament	10	10	10	10	15	15	15	15
Reserve	10	10	10	10	15	15	15	15

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 includes the date when the member registered to the platform, an array of ratings measuring coder's success in past competitions, the number of past competitions, and so on. These data are summarized in FIGURE XXXX.

FIGURE XXXX

Additional demographic information was collected via a pre-registration survey where competitors were asked their gender, age, geographic origins, education, and the most preferred programming language. Participants were als also asked their willingness to take risks "in general" (as in Dohmen et al., 2011). We also collected their forecast on the hours they expected to work on the problem in the next few days of the challenge[3]. At the end of the submission phase, competitors were also asked to fill a final suvery and looking back and tell us their best estimate of the time spent working on the problem. Also, we gathered reactions to the different competition modes with 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 NA and NA weeks as registered members. In terms of skill ratings, the distribution was highly skewed with competitors in the highest 90th percentile having participated in 28 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 **??**.

[3]The exact question was: "The submission phase begins March 08. Looking ahead a week, how many hours do you forecast to be able to work on the solution of the problem?"

Table 2: Descriptive statistics

Variable	Response Category	Frequency	Percent	P-value
country	India	33	11%	1.000
	Russia	28	9%	
	China	27	9%	
	Japan	22	7%	
	(Other)	166	56%	
	NA's	23	8%	
age	20-25 years old	94	31%	0.906
	26-30 years	78	26%	
	31-40 years	64	21%	
	41-50 years	19	6%	
	(Other)	23	8%	
	NA's	21	7%	
gender	Female	13	4%	0.505
	Male	263	88%	
	NA's	23	8%	
educ	Doctorate/PhD	27	9%	0.633
	High School	33	11%	
	Postgraduate/Master of arts	104	35%	
	Undergraduate/Bachelor's degree	114	38%	
	NA's	21	7%	
plang	C++	132	44%	0.914
	Java	82	27%	
	C#	28	9%	
	Python	25	8%	
	(Other)	12	4%	
	NA's	20	7%	

Notes: This table shows the frequency of each response category for five categorical variables: country of origin; age; gender; highest academic degree achieved; and most preferred programming language. A Pearson's Chi-squared test finds no association between each categorical variable and the treatments (p-values are reported in the last column).

Figure 1: Responses to the question about willingness to take risks "in general," measured on an eleven-point scale.

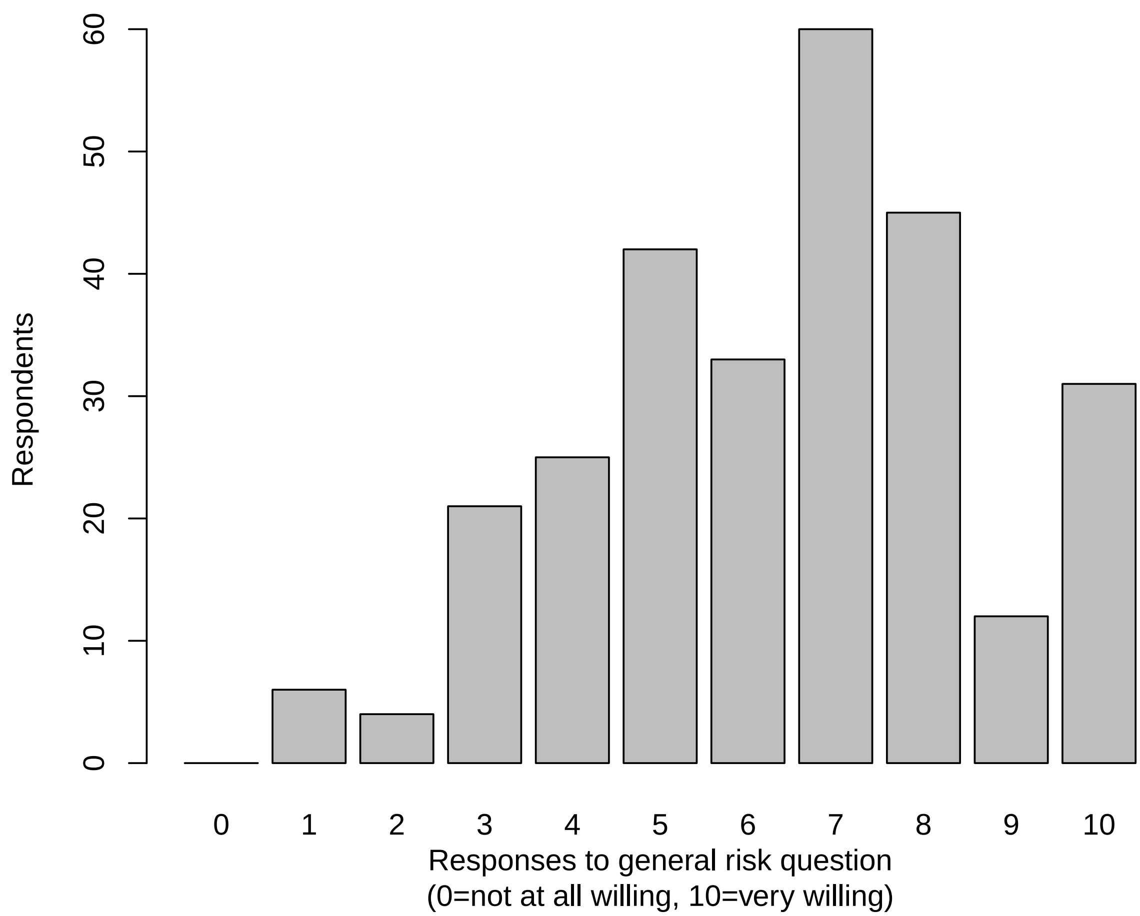


Figure 2: Responses to the question about expected hours of work for every 2 days of the competition.

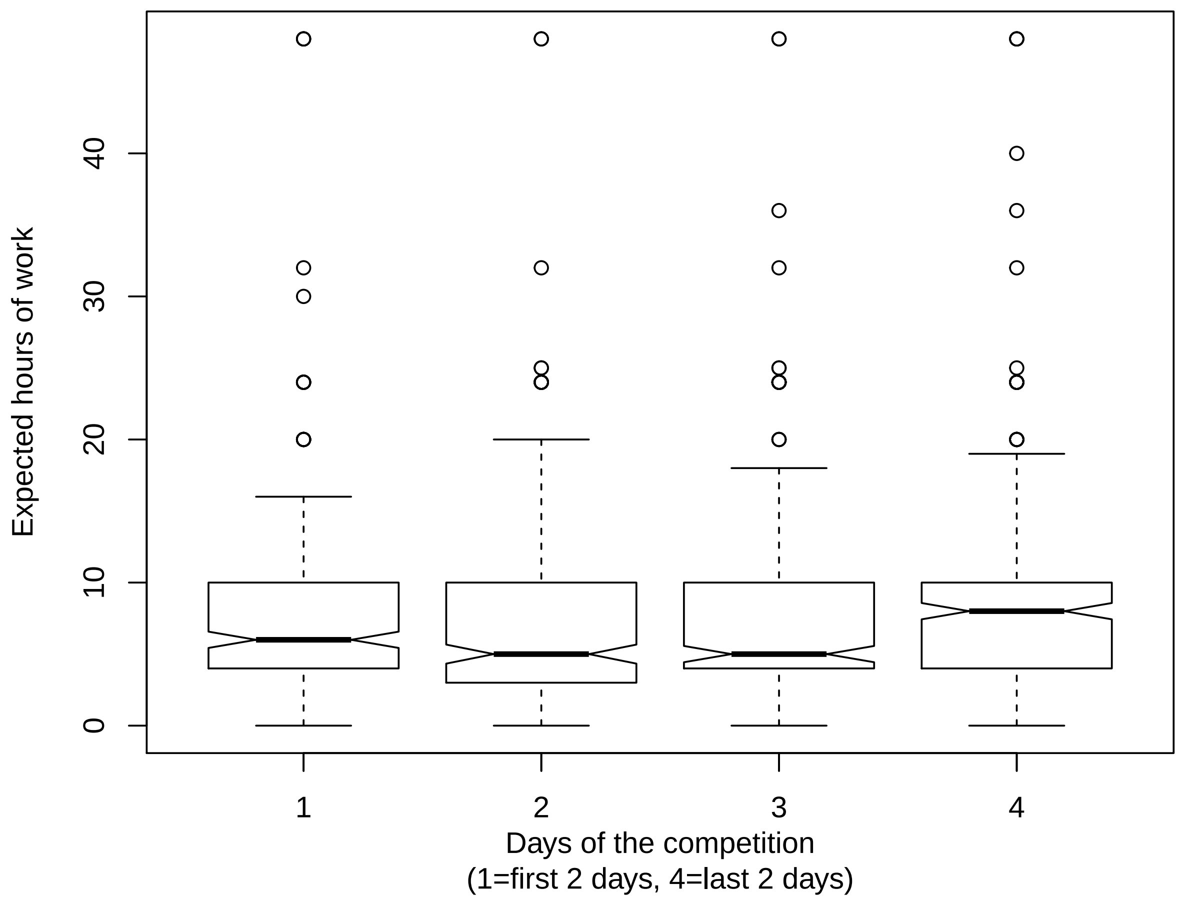
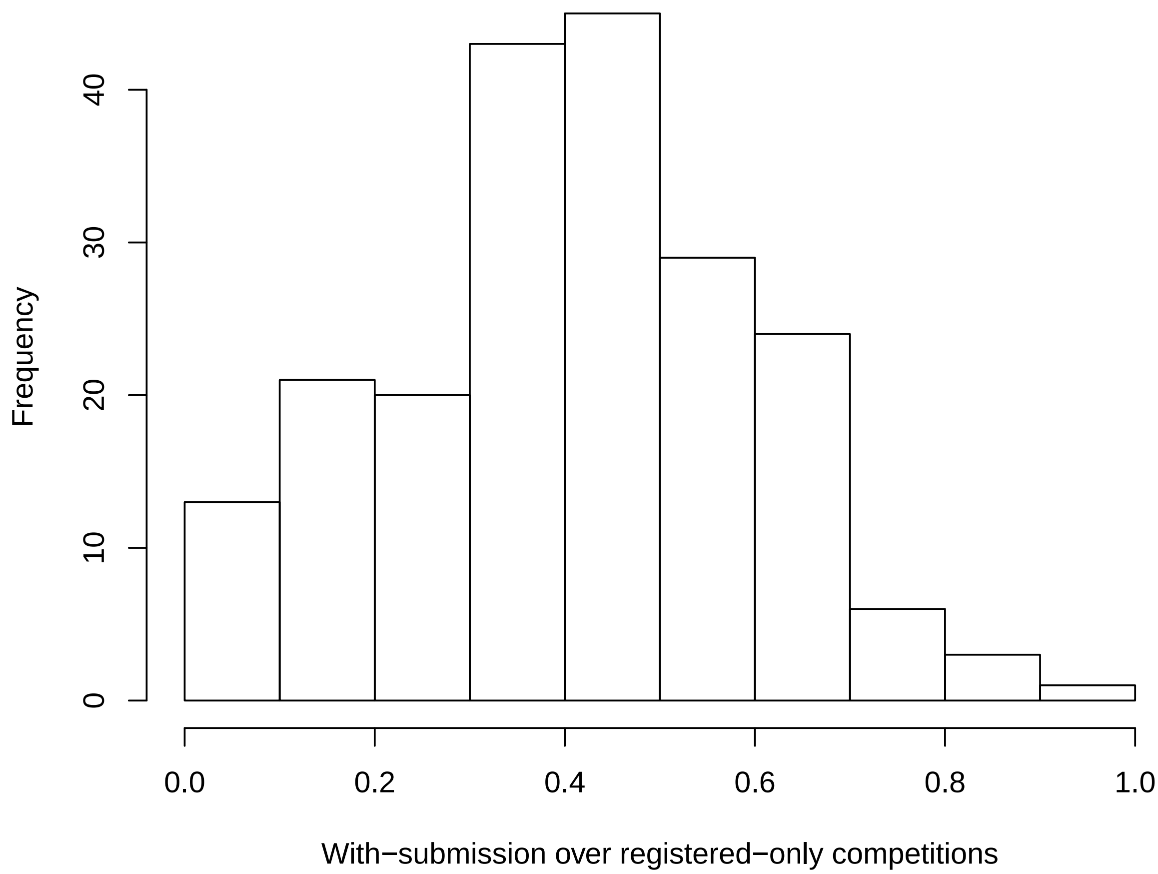
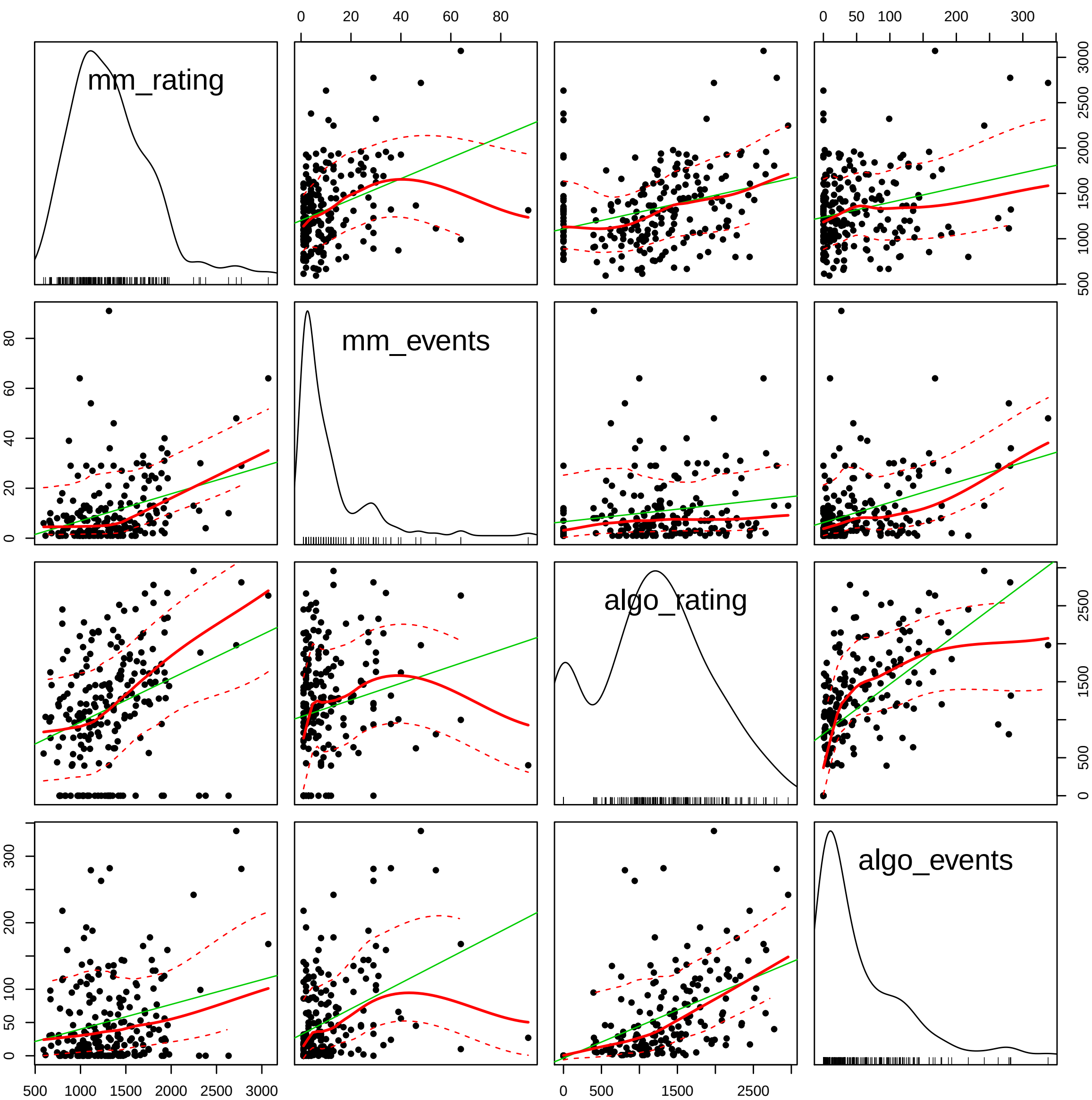


Figure 3: xxxx





5 Results

```
##
##         race tournament reserve
##   FALSE   73         67      73
##   TRUE    26         33      27
```

In the eight-day submission period, we collected a total of 1759 submissions made by 86 participants, with a median of 11 submissions per person (maximum of 126 submissions). Consistent with our prediction, the response rate was higher in the Tournament group (33 percent), followed by the Tournament w/reseve (27 percent), and the Race treatment (26 percent). Though the association between treatment and response rates was not statistically significant (a Fisher's Exact Test for Count Data gives a p-value of 0.526).

```
##
##          Large Small
##   FALSE    128    85
##   TRUE      52    34
```

We find no difference between participation in large or small rooms (a Fisher's Exact Test for Count Data gives a p-value of 1).

```
##               race tournament reserve
##
## Large FALSE     44         42      42
##       TRUE      16         18      18
## Small FALSE     29         25      31
##       TRUE      10         15       9
```

We also find no evidence of an overall association between treatments, room size and participation (a Fisher's Exact Test for Count Data gives a p-value of 0.86).

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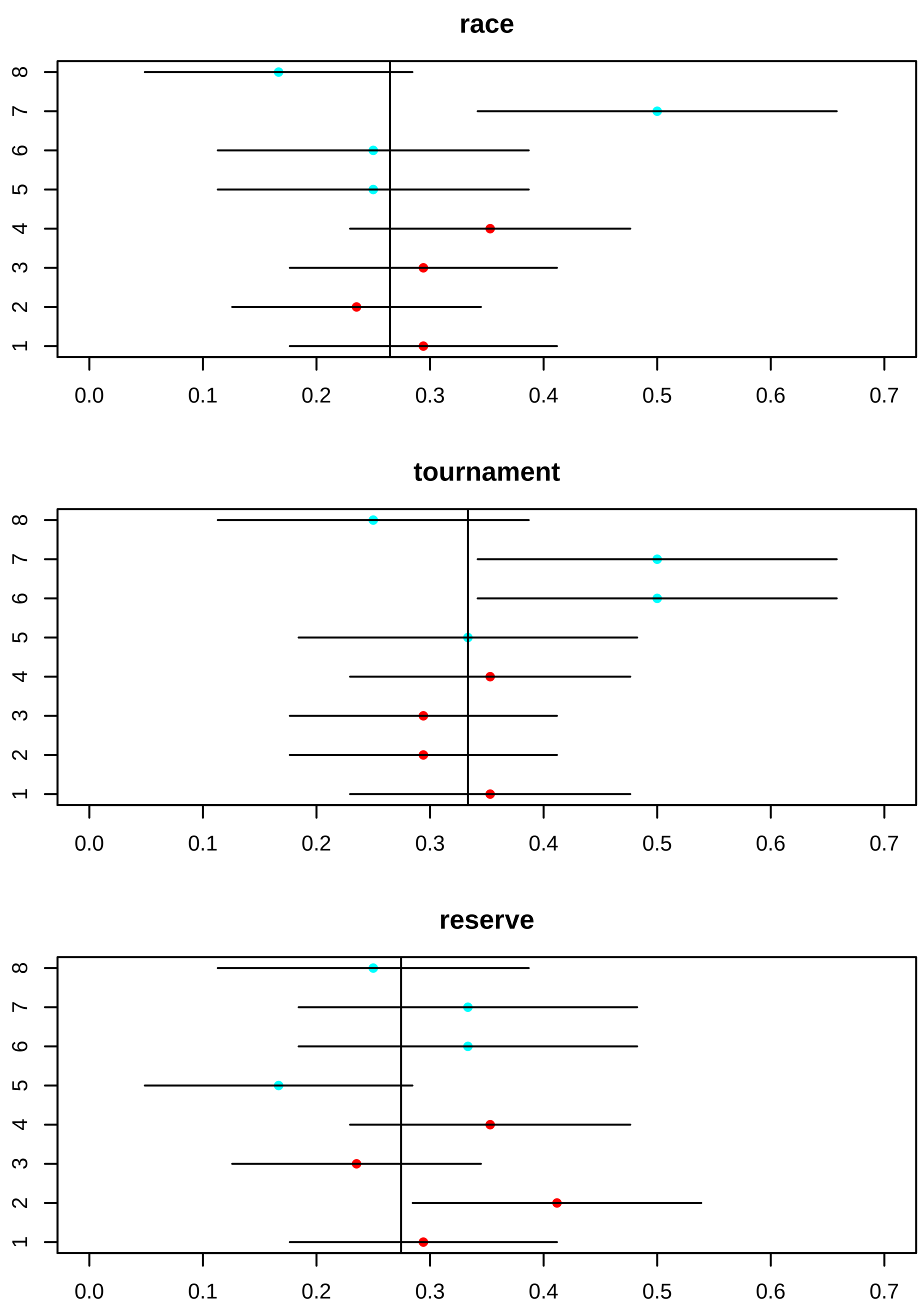
Figure 4: Participation rates by rooms



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