Races or Tournaments?*

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Abstract

A wide range of economic and social situations are decided by either a race or a tournament. In either situations, agents choose whether and how much to exert some costly effort to increase the probability of being awarded a prize under the uncertainty about the actions of other agents. While a tournament yield outcomes greater than those of a race, the latter prevents unnecessary costs due to an excess of participation. We examine this trade-off empirically. We report the results of a field experiment conducted online where we compare the outcomes — efforts, quality, and diversity of outputs — of three alternative competitive situations motivated by theory: the race, the tournament, and the tournament with a quality requirement.

JEL Classification: xxx; xxx; xxx.

Keywords: xxxx; xxxx xxxx.

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Contents

1 Introduction

Organizations use often prizes as incentive schemes for innovation. In the United States, the government routinely sponsors open calls for innovation projects tackling important issues of public policy (public health, education, environment protection) where participants compete to finish a project, and the winners, if any, are awarded a prize. The same happens inside firms where internal contests are used to expand the innovative capacity of the firm by stimulating workers ideas. Or open contests are sponsored to source ideas from people outside the boundaries of the organization, e.g., members of online communities (xxx).

Typically, the objective of the contest designer is to maximize the quality and probability of a succesfull innovation while minimizing the time it takes to complete the project. This problem of contest design has been long investigated. However, one key factor that has received relatively less attention is the choice of how participants compete. In general, there are two extreme forms of competitions. One is the race where the participants who first finish the innovation project win. The second is the tournament where the participants to finish the project within a deadline are then ranked by quality and the top-ranked ones win, regardless of their timing. If the contest designer wants to minimize the time it takes to complete the project, one option is to set a tournament with a tight deadline hoping that competitors will reach a successful innovation by that time. One problem with this approach is that the tight deadline may reduce participation, lowering the intensity of the competition and, therefore, minimizing the expected quality of the innovation. The alternative is to fix the quality, and let participants compete on xxx.

Under a contest design perspective, the choice of which format to use is complicated. A first difficulty is with regard to how the competition format affects participants' motivation and behaviors. If the competition is a race, the goal is given and only those who expect to complete the project in a reasonable time will participate in the competition. In a tournament, by contrast, the quality of the project is determined during the contest. In principle anyone could win. However, one must confront not only with the issue of how participants will respond but also with respect to what would be optimal for the contest designer. While both issues has received much attention, the comparison of races and tournaments from a contest designer perspective remains largely unexplored.

To be sure, there exist many models of races and tournaments that have been applied to a wide range of economic situations: patent races, arms races, sports, promotions inside firms, sales tournaments. However, 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.

To fix ideas let consider an example. Suppose the government wants to find a solution an increasing threat for public health such as the antibiotic resistance problem: the overuse of antibiotics leads to a loss in the power of antibiotics to treat certain infections. To do so, the government wants to engage a large and diverse crowd of potential problem-solvers from around the world. The government wants the solution to be as xxx as possible but it also wants to minimize the time to have any solution. The choice is between a tournament with a fixed deadline and a race with a fixed solution quality award a prize to the first to meet this requirement. For example, the UK government adoptes a race setting. Whereas the EU adopted a tournament setup.

In this study, we design and execute a field experiment to compare behavior in a race and a tournament setting. To address these questions we proceed in two ways. First, we generalize the well known incomplete information contest model of Moldovanu and Sela (2001). This is enables a direct comparison of equilibrium behaviors under both the race and the tournament within a single theoretical framework. Then, we collect data from a field experiment that we desiged and run to test some of the implications of the theory, and provide policy recommendations.

3.1 Problems of inefficiency (discriminating)

3.1.1 Excess of effort 3.1.2 Excess of participation

3.2 Duality

3.3 Maximizing revenues (what about timing)

4. Our experiment

The field experiment was conducted xxxx. 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). Submissions were made online. The top submissions were awarded a monetary prize ranging between $5000 to $100 for a total prize pool of $40,000.

[This context is relevant in itself.] Programming competitions are a very important source of incentives in the economy. In the United States, the government routinely sponsors open contests to tackle a variety of issues of public health, education, energy, environment protection, and so on. A large part of which are conducted online through the web portal Challenge.gov. Contests are also used extensively by non-profits (xxxx) and in the private sector by sourcing ideas from outside the boundaries of the organization.

4.2 Treatments

Competitors were randomly assigned to 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 by the platform for a submission to be awarded a prize.

5. Results

By this perspective, we are able to show that races cannot be justified simply by the goal of maximizing average effort. And the reason is intuitive. A race awards a prize to first to hit a particular target. Those who will judge the target to hard to achieve will not join the competition and will drop out. On the contrary, those who are able to achieve the target at low costs will not try to exceed the target. As a result, the race is comparable to a competition with fixed "entry costs" or a fixed entry requirement, where agents will decide to either enter and pay a fixed prize, or stay out of the competition. Then, the possible gains in terms of expected revenues from a race are limited to those who would enter the competition and would exert less effort that that required to hit the target. These potential benefits can be obtained under a tournament as well by imposing a a fixed requirement to be eligible for prizes. So, races are not chosen to maximize expected effort of competitors, at least, in the traditional "auction-theoretical" sense.

In a tournament, this type of preferences can be satisfied by fixing a deadline. Say time within which competitors are asked to provide their efforts. However, assuming competitors have costs from making less time in performing a task and there complementarities in costs, increasing the deadline in a tournament is similar to raising the marginal cost for everyone, which might not be an optimal solution. In a race, by contrast, increasing the deadline will affect entry but, conditional on entry, the time to complete the task will always be less than the deadline. Which means that those with low costs will be mostly affected by the deadline, whereas xxxx. Which may be a superior choice than the tournament.

We find that, as our theory suggest, participation is higher in the tournament and lower in the race and in the tournament with entry costs. We further find that 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. With respect to final scores, theory predicts as 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).

3 The model

We generalize the contest game described by Moldovanu and Sela (2001) to a situation where N players decide how much effort to provide along two dimensions: performance and time. The contest game is an N player game with asymmetric information. Players move simultaneously to maximize the expected utility. Each player $i = 1, 2, ..., N$ selects a performance variable y_i and a timing t_i, both being nonnegative numbers. These variables can be thought of as the accuracy of a solution to a given problem and the time to write the code implementing such solution. Players incur a cost from effort given by the function

$$C_i(y_i, t_i) = \frac{1}{a_i} c(y_i, t_i) \tag{1}$$

where the function $c(\cdot)$ is xxxx. The cost parameter a_i denotes the player's ability, which is privately observed at the beginning of the game. It is common knowledge that abilities are drawn from a common distribution F that is continuous on the semi-infinite interval $[0, \infty)$ (e.g., exponential).

Let r_i denote the rank position of a player i relative to the $N-1$ others. The top K players (e.g., $r_i \leq K$) are awarded a prize of value $V_1 > V_2 > ... > V_K$. A player's probability of winning a prize is given by the function $p_i(y_1, ...y_N, t_1, ..., t_N)$.

The goal for each player is If the timing is above a given deadline $d > 0$ or the performance is below a certain level $q > 0$, the player gets zero utility. Otherwise, the player is given a rank based on his performance and timing. A contest is xxxx. Ranked .

def: A tournament is a xxxx where players are ranked by their performance level provided that the timing is below a deadline d.

def: A race is a xxxx where players are ranked by their timing provided that the performance is above a threshold level q.

In a tournament, the agent having achieved the highest output quality within the deadline gets the first prize, the agent having achieved the second highest output quality gets the second prize, and so on. In a race, by contrast, the first agent to achieve an output quality of at least $\bar{y}$ within the deadline wins the first prize, the second to achieve the same target gets the second prize, and so on.

Since agents move simultaneously, they do not know the performance of others when deciding their efforts. On the other hand, it is assumed that they know the number of competitors as well as their cost functions to complete the task up to a factor a_i being the agent's private ability in performing the task. Each agent knows his ability but does not know the ability of the others. However, it is common knowledge that abilities are drawn at random from a common distribution F_A that is assumed everywhere differentiable on the support $V \subseteq [0, \infty)$.

It is further assumed that costs are multiplicative

$$C(y_i, t_i, a_i) = c_y(y) \cdot c_t(t) \cdot a_i^{-1}$$

with $c_y(0) \geq 0$, $c_y{}' > 0$, $c_t(d) \geq 0$, and $c_t{}' < 0$.

Each agent is risk neutral and faces the following decision problem

$$\text{maximize} \quad \textstyle\sum_{j=1}^{k} \Pr(\text{ranked } j\text{'th}) V_j - C(y_i, t_i, a_i).$$

3.0.1 Equilibrium

We provide here the symmetric equilibrium with one prize and $n > 2$ agents. In appendix XXX, we provide a general formula for $k > 2$ prizes.

Let $y_{1:n} < y_{2:n} < ... < y_{n:n}$ denote the order statistics of the y_j's for every $j \neq i$ and let $F_{Y_{r:n}}(\cdot)$ and $f_{Y_{r:n}}(\cdot)$ denote the corresponding distribution and density for the r'th order statistic.

Proposition 1. *In a tournament, the unique symmetric equilibrium of the model gives, for every $i = 1, ..., n$, the optimal time to completion $t^*(a_i)$ equal to the deadline d and the optimal output quality $y^*(a_i)$ as*

$$y^*(a_i) = V_1 \int_{a_i}^{\infty} f_{Y_{n:n}}(z) dz$$

if $a_i \geq \underline{a}$ (see Moldovanu and Sela, 2001), and equal to zero otherwise.

An important property of is that $y^*(a_i)$ has its upper bound in and lower bound in . 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

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

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

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

Corollary 1. *Equilibrium behavior in a race*

3.0.2 Contest designer's problem

The sponsor of the contest chooses the rules of the competition including prize structure $\{V_j\}_{j=1}^k$, deadline d, target quality q, and competition format (race or tournament). The sponsor maximizes an objective function that is the sum of total quality $Y = \sum_{i=1}^{n+1} Y_i$, time spent $T = \sum_{i=1}^{n+1} T_i$ and prizes paid $V = \sum_{j=1}^{k} p_j V_j$ (with $p_j = 1$ if the prize is awarded and $p_j = 0$ otherwise). Hence, the problem faced by the sponsor is

$$\text{maximize} \quad \int Y - \tau \mathbf{E} T - \mathbf{E} V$$

with the intensity of preferences towards time weighted by $c_t \geq 0$.

3.1 Structural econometric model

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 where participants compete writing a programming code that solves a designated problem. Similar programming contests are quite common and 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.

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.

Table 2: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Algo rating	299	$1,051.000$	730.000	0	$2,958$
Algo competitions	299	40.600	57.700	0	338
Algo registrations	299	45.700	64.300	0	365
MM rating	205	$1,322.000$	425.000	593	$3,071$
MM competitions	299	7.160	11.800	0	91
MM registrations	299	17.600	23.000	1	161
Time zone	279	2.130	5.080	-8.000	10.000
Latitude	279	36.700	19.000	-42.800	59.900
Longitude	279	25.200	77.700	-122.000	149.000
Risk aversion	284	6.390	2.190	1	10

5 Results

A total of xxxx registered but only 299 competitors were selected for the challenge; we excluded those with no past experience on the platform and those with incomplete data on the survey. Signed up competitors were experienced members of the platform: the overall time as registered platform member at the start of the competition ranged between 52.542 and 770.548 weeks. Yet, the direct experience in competing 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 **??**.

After the two-week submission period, 86 competitors made 1759 submissions overall. The distribution of submissions was rather skewed, with participants in the 90th percentile making 50 more submissions than those in the 10th percentile.

Assuming the decision was independent, to explore the determinants of participation:

$$Pr(y = 1) = G(\text{Rating}_i + \text{Experience}_i + \text{T}_i) \tag{2}$$

where $G()$ is logistic.

```
##
## ==========================================================
##                                 Dependent variable:
##                           -------------------------------
##                                       submit
##                              (1)        (2)        (3)
## ----------------------------------------------------------
## 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*     4.980*
##                                      (2.540)    (2.590)
##
## poly(mmevents, deg = 2)2             -0.212     -0.077
##                                      (2.470)    (2.530)
##
## poly(mmrating, deg = 2)1            10.100***  8.530***
##                                      (3.120)    (3.260)
##
## poly(mmrating, deg = 2)2             -0.942     -1.500
##                                      (2.380)    (2.430)
##
## lat                                             0.021**
##                                                 (0.009)
##
## long                                             0.003
##                                                 (0.002)
##
## Constant                  -0.961*** -1.020***  -1.900***
##                            (0.138)   (0.143)    (0.405)
```

```
##
## ------------------------------------------------------
## Observations                 299       299       279
## Log Likelihood            -166.000  -164.000  -150.000
## Akaike Inf. Crit.          341.000   337.000   315.000
## ======================================================
## 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                                       278        334
## poly(mmevents, deg = 2)  2    17.87        276        316  0.00013
## poly(mmrating, deg = 2)  2     8.89        274        308  0.01172
## lat                      1     4.96        273        303  0.02589
## long                     1     1.85        272        301  0.17347
```

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$submax <- ave(subs$sub_id, subs$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')
```

Scores: xxxx

5.1 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.

5.2 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.

5.3 Simulation results

6 Empirical analysis

6.1 Estimation results

Participation to the competition by treatment is shown in Figure

$$fig : entry$$

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6.2 Simulation results

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