Optimal Contests with Negative Prizes: Theory and Experiment*

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Abstract

This paper examines the optimal design of contests in the presence of negative prizes and establishes the optimality of a *modified* all-pay auction with entry fee and reserve. The entry fee always equals the contestants' liability, and the reserve is weakly higher than in contests without negative prizes. The modification involves awarding all contestants a strictly positive prize if none meet the reserve. This optimal contest better incentivizes high-ability contestants by offering them a higher prize augmented by entry fees, while still ensuring full participation from low-ability contestants. Theoretical analysis demonstrates that when contestants' liability is sufficiently high, the same contest maximizes both the expected total effort and winner's effort, with both measures increasing with liability. Numerical simulations show that even with low liability, predictions from the two optimal contests are closely aligned. To test these predictions, we conduct an experiment comparing optimal contests across different liability levels, confirming the "killing-two-birds-with-one-stone" prediction.

Keywords: Entry Fee, Laboratory Experiment, Liability, Mechanism Design, Optimal Contest, Prize Allocation

JEL Codes: C72, C91, D82, J43, M52

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1 Introduction

In 1990, the Federal Communication Commission (FCC) organized an open contest requiring a \$20,000 entry fee to determine the American broadcast standard for high-definition television. In such traditional contests, contestants simultaneously decide whether to participate by paying an entry fee, with winners determined by rankings upon meeting a reserve. However, low-ability contestants may be discouraged from participating, as paying the entry fee without winning yields a negative prize of -\$20,000. While conventional auction design theory by Myerson (1981) suggests that excluding low-ability contestants is in the contest designers' interest, recent research by Liu et al. (2018) shows that when negative prizes are allowed and can augment the whole prize, inducing full participation becomes optimal. Liu et al. (2018) focus on contests designed to maximize the (expected) total effort, but this objective may not always align with the contest designer's primary goals. In many real-world settings, maximizing the (expected) winner's effort is often more critical. For instance, in research tournaments such as the FCC example, it is the best performance rather than the collective effort that determines success (Taylor, 1995). Similarly, crowdsourcing platforms like Indiegogo and InnoCentive prioritize the quality and feasibility of the final innovation or solution over the aggregate contributions of participants. Other examples include competing legislative bills that shape laws, lobbyists crafting persuasive policy proposals, politicians striving to win elections, lawyers building compelling evidence for court cases, and citizens submitting competing urban development projects to their municipality, as detailed in Serena (2017). Yet, in some situations, the designer may need to balance maximizing the winner's effort and total effort. For example, the Netflix Prize (https://www.netflixprize.com/rules.html), established in 2006, aimed to identify the best algorithm for predicting user ratings of films. While Netflix's primary goal was to implement the best algorithm (maximizing the winner's effort), it also valued broad engagement from participants in generating a variety of new algorithms (maximizing the total effort). Such dual objectives highlight the complexity of contest design in practical applications.

This paper contributes to the literature by proposing a contest design that can almost always achieve the dual objectives simultaneously, making it highly versatile and adaptable to diverse design needs. Theoretically, we extend the Liu et al.'s (2018) framework to derive the optimal contest for maximizing the *winner*'s effort when negative prizes are allowed. We find that the optimal contest for maximizing the winner's effort has a structure similar to the contest for maximizing the total effort and can be implemented by a modified all-pay auction with entry fee and reserve. In this optimal structure, the entry fee is set at contestants' liability, and the reserve is weakly higher than in contests without negative prizes. The key modification involves allowing all contestants to receive some prizes when no one meets the reserve. This design induces full participation and provides stronger incentives by topping up the prize budget with the entry fees. Surprisingly, if contestants' liability is sufficiently high, the same contest achieves the dual objectives of maximizing the total effort and the winner's effort. Furthermore, a large set of numerical simulations indicate that even when contestants' liability is low, the predictions from the two contests optimally designed for maximizing the winner's effort and maximizing the total effort, respectively, are quite close. This implies that designers can achieve both goals to a reasonable extent with either optimal contest for any liability level. To the best of our knowledge, this "killing-two-birds-with-one-stone" result has not been reported previously in the contest literature. We also find that both total and winner's effort increase with the size of the liability. Additionally, we deepen the theoretical investigation by examining the roles of risk aversion. Experimentally, we present the first study testing the proposed contest design in a controlled laboratory setting, evaluating its effectiveness in achieving the dual objectives of maximizing both total effort and winner's effort. Our results show that the aggregate outcomes of our optimal contests align closely with the theoretical predictions.

A notable feature of the theoretically optimal contest structure is that if all contestants' efforts fall below a certain threshold, the prize budget (or a portion of it) is equally distributed among them. This feature aims to encourage participation from lower-ability contestants, thereby enabling transfers from these individuals to those with higher abilities through negative prizes. This prize structure closely resembles the performance-based pay structure adopted by many university departments worldwide where salary supplements or bonus pay are part of a collective pool distributed based on departmental level performance. Specifically, when no individual faculty member meets performance criteria, the departmental funding pool for such bonuses are distributed equally among all members rather than being forfeited

More specifically, to test the theoretical properties of the optimal contests, we conduct a lab experiment with four different liability levels. The experiment includes six treatments: High_TW, Medium_TW, Low_W, Low_T, Zero_W and Zero_T, where High, Medium, Low, and Zero represent the levels of liability, and T and W indicate whether the contest theoretically aims to maximize the total effort or the winner's effort. The treatments with high or medium liability are designed to maximize both total effort and winner's effort. In contrast, the four treatments with low or zero liability cannot theoretically achieve both objectives, so they represent different goals of maximizing the total effort or the winner's effort. Notably, the two treatments with zero liability serve as benchmarks where negative prizes are not allowed. Importantly, after extensively exploring a wide range of parameterizations, we find that the predicted effort differences between the two different optimal designs with different objectives are relatively small when contestants' liability is low or zero, making them difficult to detect statistically in lab experiments. Therefore, the proposed contest structure with negative prizes not only achieves the joint objective of maximizing both winner's effort and total effort when contestants' liability is sufficiently large, but it also "almost" achieves this goal even when liability does not exceed the theoretical threshold.

Overall, the aggregated results from our lab experiment show that the winner's effort and total effort are remarkably close to the predicted levels across all treatments. In the High_TW treatment, the winner's effort is 45.8% greater compared to the baseline treatment Zero_W, and the total effort is 48.5% greater compared to the baseline treatment Zero_T. The Medium_TW treatment also produces greater winner's effort and total effort relative to treatments with low or zero liability, although these improvements are not statistically significant. This finding confirms our prediction that induced effort monotonically increases in liability. However, we observe deviations in individual behavior from the theoretical prediction. While the theory predicts full participation in the optimal contest, the actual participation rate is much lower. Specifically, the low participation rate is primarily driven by low-ability contestants. By contrast, high-ability contestants enter the contest over 90% of the time when the liability is high, but they tend to provide lower efforts than the predicted levels.

To further investigate the deviations in individual behavior, we first conduct additional theoretical analysis, demonstrating that non-entry decisions can be rationalized by our mechanism when considering risk-averse players. Consistent with the theoretical analysis, our experimental data provide support for the role of risk attitudes in influencing entry decisions. Then, we conduct an additional treatment based on the High_TW treatment. The only difference is that participants are forced to enter the contest during the first 10 rounds. After that, they are free to decide whether to continue entering the contest, as in the original High_TW treatment. The design of mandatory entry aims to simplify participant's decision-making and allow them to focus solely on their effort choices.

Our findings indicate that forcing players to enter the contest does not align their behavior with theoretical predictions. However, the experimental data provide insights into the observed behavioral deviations. In particular, the underprovision of effort by high-ability players can be fully explained by their beliefs about the intensity of competition. We also find that the experience of forced entry has little impact on players' behavior during the last 10 rounds when they are free to opt out of the contest. This suggests that our original findings from the High_TW treatment are highly robust and, crucially, that opting out of the contest is a deliberate choice rather than a mistake. Indeed, by comparing the realized payoffs between the first and last 10 rounds, we find that low-ability players are better off by not entering the contest. Thus, the decision of low-ability players to refrain from entry is empirically rational. This finding is further supported by a counterfactual analysis of low-ability players' payoffs, utilizing data from the High_TW treatment. Hence, risk aversion, negative experience associated with entering the contest, and players' beliefs about the intensity of competition can collectively help explain the observed behavioral deviations.

Contests with negative prizes, which act as sticks in addition to carrots to motivate effort, have received considerable attention in the recent literature. Similar to Fullerton and McAfee (1999), Liu et al. (2018) and Hammond et al. (2019), we assume that negative prizes can be used to supplement the prize budget. Our theoretical model closely follows Liu et al. (2018) in deriving the optimal contest for maximizing the winner's effort using the mechanism design approach.[1] Several papers assume that negative prizes cannot be used to supplement the prize budget. The most comprehensive study is Liu and Lu (2023) who allow for a general setup and find that the optimal

[1]Note that while this approach has been adopted by Polishchuk and Tonis (2013) to rationalize the Tullock success function, Chawla, Hartline and Sivan (2019) to derive the optimal contest for maximizing the winner's effort, and Kirkegaard (2012) to study the optimal favoritism with asymmetric players, none of these papers consider the inclusion of negative prizes.

prize structure comprises a winner-take-all prize for the best performer and, at most, one negative prize for the worst performer among all potential contestants, whenever they enter the competition. Prior to Liu and Lu (2023), previous works imposed additional assumptions on the prize structure, such as the number of positive prizes, the number of negative prizes, and uniform negative prizes. For instance, Thomas and Wang (2013) and Kamijo (2016) assume a single positive prize for the best performer and a single negative prize for the worst performer among all players who enter. Moldovanu, Sela and Shi (2012) assume a single positive prize for the best performer and a fixed number of uniform negative prizes for the lowest entrants.[2]

Our paper also contributes to the experimental literature on contests (see Dechenaux, Kovenock and Sheremeta (2015) for a comprehensive review, and Sisak (2009) for a review specifically on multiple-prize contests), particularly contests under incomplete information, which have received relatively limited attention (Noussair and Silver, 2006; Müller and Schotter, 2010; Liu et al., 2014; Boosey, Brookins and Ryvkin, 2017). Boosey, Brookins and Ryvkin (2020) study contests with endogenous entry and an outside option (which can be interpreted as an entry fee), testing the impact of disclosing the number of contestants on individual effort. Hammond et al. (2019) examine the effect of an optimal prize-augmenting entry fee on the total effort in all-pay auctions when individual ability is private information. It is important to note that such an all-pay auction with an entry fee is sub-optimal on its own as it discourages low-ability contestants from participating. Compared to these previous works, our experiment implements the optimal contest and extends the focus to both the winner's effort and the total effort. We are the first to test the effectiveness of this optimal contest in a controlled experiment.

2 Optimal contests

We adopt the framework proposed by Liu et al. (2018). A risk-neutral contest designer has a total prize budget of $V > 0$ to elicit effort from $N \geq 2$ risk-neutral contestants. Each contestant may differ by his ability to compete in the contest. The cost for contestant i with ability t_i to exert effort $e_i \geq 0$ is given by $c(e_i, t_i) = e_i/t_i$. This ability or type t_i is private information known only to contestant i. The ability follows an independent and identical distribution with a cumulative distribution function $F(\cdot)$ and a probability density function $f(\cdot)$. The support of the ability lies in the interval $[a, b]$, where $a > 0$ and b is the maximum ability.

The payoff of a contestant is equal to the prize he receives minus his cost of effort. The contest designer uses the prize budget V to incentivize effort from the contestants. Additionally, if there is money left in the budget, the designer values that money as well. For simplicity, we assume a linear

[2] There is a substantial body of literature on optimal prize structures in contests where negative prizes are not permitted. Moldovanu and Sela (2001) pioneer this line of research by adopting the the model of all-pay auctions under incomplete information. Their work has since been extensively extended, including studies by Minor (2012), who examines the role of convex costs of effort, Olszewski and Siegel (2020), who consider large contests with risk averse contestants and convex cost functions, Moldovanu and Sela (2006), who consider multiple-stage all-pay auctions and Moldovanu, Sela and Shi (2007), who assume that contestants care about relative status.

relationship between effort and money for the contest designer. Let $1/t_0$ represent the marginal benefit of effort for the contest designer, with t_0 being common knowledge. It is important to note that the cost of 1 unit of effort for a contestant with the maximum ability (b) is $1/b$, which needs to be less than $1/t_0$ to make it optimal for the designer to allocate at least some of the prize budget. Hence, we assume that $t_0 < b$.

One distinctive feature of this paper is that negative prizes are allowed. Contestants have limited liabilities or endowments, so there is a bound $K \geq 0$ for the negative prize. Using a mechanism design approach, Liu et al. (2018) have fully characterized the optimal contest for maximizing total effort among symmetric mechanisms. When $K = 0$, the problem is equivalent to the well-known one presented by Myerson (1981), and the optimal mechanism involves allocating the entire budget to the contestant with the highest virtual ability if it exceeds a cutoff. However, when $K > 0$, the designer has an incentive to collect negative prizes from contestants and then "top up" the final prize pool to create a larger payoff gap between winners and losers, thus providing stronger incentives. The challenge, however, is that low-ability contestants anticipate having little chance of winning and receiving a negative prize, which discourages their participation. The innovation of the optimal contest in Liu et al. (2018) is that when no one's ability exceeds a certain cutoff, everyone receives the same positive prize. As a result, low-ability contestants receive zero prize in expectation and are indifferent between participating and not participating.

Liu et al. (2018) demonstrate that the optimal contest can be implemented through a class of simple contests, namely modified all-pay auctions with entry fee and reserve. This class of contests nests the standard all-pay auction with a reserve as a special case. Contestants simultaneously decide whether to pay an entry fee E and how much effort to exert in the contest upon entry. If the highest effort among the contestants exceeds a threshold (the reserve) $\hat{e}$, then the best performer receives V plus all the collected entry fees, while others receive zero. Otherwise, all contestants receive the same shared prize $S \in [E, E + V/N]$. When $E = 0, S = 0$, this reduces to the standard all-pay auction with a reserve $\hat{e}$. When $E > 0$, this contest features a negative prize, as the prize for a contestant who chooses to enter and loses to a participant with effort higher than the threshold is $-E < 0$. The limited liability constraint implies that the entry fee cannot exceed any contestant's liability, i.e., $E \leq K$. This class of simple contests is characterized by three parameters $(E, \hat{e}, S)$.

We aim to find the optimal contests by selecting appropriate values for $(E, \hat{e}, S)$. While the designer's objective in Liu et al. (2018) is to maximize the total effort, we are also interested in maximizing the winner's effort, as mentioned in the introduction. Let $D \in \{T, W\}$ denote one of the objectives. We define the virtual ability functions $J^T(t) = t - \frac{1-F(t)}{f(t)}$ and $J^W(t) = tF(t)^{N-1} - \frac{1-F(t)^N}{Nf(t)}$ under the two objectives, respectively. Intuitively, the virtual ability function $J^T(t)$ represents the situation where the designer knows a contestant's ability t, allowing the designer to extract t units of effort with 1 dollar. However, since t is privately known by the contestant, the designer needs to provide informational rent to the contestant. The virtual ability is simply the difference between the true ability and the informational rent. The virtual ability function $J^W(t)$ follows the same logic, but in this case, the designer only cares about the contestant's effort if he becomes the winner, which occurs with probability $F(t)^{N-1}$.

We can define a threshold ability as $t^{*D} = \max\{J^{D-1}(t_0), F^{-1}((\frac{NK}{V+NK})^{\frac{1}{N-1}})\}$. The following proposition reproduces the results in Liu et al. (2018), extends their approach to derive the optimal contest for maximizing the winner's effort, and explains the relationships between the two optimal contests. All proofs are presented in Online Appendix A.

Proposition 1 *In the contest for maximizing the total effort (D=T) and for maximizing the winner's effort (D=W), we have*

$$\hat{e}^D = t^{*^D} \left\{ [V + (N-1)K] F(t^{*^D})^{N-1} - K \left[1 - F(t^{*^D})^{N-1} \right] \right\} \tag{1}$$

$$E^D = K \tag{2}$$

$$S^D = \frac{K}{F^{N-1}(t^{*D})} \tag{3}$$

If $K \geq \frac{VF(J^{W-1}(t_0))^{N-1}}{1-F(J^{W-1}(t_0))^{N-1}}$*, the same contest achieves both objectives.*[3]

It is important to note that the difference between the two optimal contests is captured by the threshold ability t^{*^D} only. The two optimal contests share the same entry fee, which is equal to the contestants' liability K. The entry fee allows the designer to provide stronger incentives by topping up the prize, so it is natural to use it to the maximum extent, i.e., up to the limit K, for both objectives. The reserve E^D is increasing and the shared prize S^D is decreasing in the threshold ability t^{*^D}. Intuitively, to achieve a higher threshold ability t^{*^D}, a higher reserve is needed, resulting in a higher probability of sharing the prize. To provide sufficient participation incentives for low-ability contestants in this case, a lower equally shared prize is needed. It is easy to see that the cutoff for winner effort maximizing should be weakly higher than that for total effort maximizing, since the winner is the one with the highest effort and the designer can use a higher standard. As a result, the reserve is weakly lower and the equally shared prize is weakly higher, i.e., $E^T \leq E^W$ and $S^T \geq S^W$.

Notably, when the liability is substantial, i.e., $K \geq \frac{VF(J^{W-1}(t_0))^{N-1}}{1-F(J^{W-1}(t_0))^{N-1}}$, we have $t^{*^T} = t^{*^W}$. In this situation, the two optimal contests coincide with each other, meaning that the same contest achieves the dual objectives of maximizing both the total effort and the winner's effort. For intuition, note that the cutoff is determined in a way such that contestants with type lower than the cutoff are getting zero prize in expectation. On one hand, they equally share a proportion of the (positive) prize when no one's type is higher than the cutoff which happens with probability $F(t^{*^D})^{N-1}$;

[3] Liu et al. (2018) show that the contest $(\hat{e}^T, E^T, S^T)$ maximizes the total effort among all symmetric mechanisms. In contrast, such a stronger result cannot be established for maximizing the winner's effort. As mentioned in the conclusion of Liu et al. (2018), if any mechanism is allowed, the optimal mechanism in maximizing the winner's effort will feature winner pay only. However, such a mechanism does not fall into the class of contests we focus on since losers also need to pay for their effort. Nevertheless, $(\hat{e}^W, E^W, S^W)$ is optimal among mechanisms where one's effort cannot depend on others' abilities.

on the other hand, they obtain a negative prize $-K$, otherwise. The designer can adjust both the magnitude of the shared prize and the cutoff to maintain a zero prize in expectation. The first one is less costly for the designer since she mainly cares about effort ($t_0 < b$). When K becomes large, the shared prize is already set at its maximum, the prize itself, and the only choice is to move up the cutoff. As a result, regardless of the objective, the cutoff is determined by $\frac{V}{N}F(t^{*^D})^{N-1} - K(1 - F(t^{*^D})^{N-1}) = 0$. When K is small, i.e., $K < \frac{VF(J^{W-1}(t_0))^{N-1}}{1-F(J^{W-1}(t_0))^{N-1}}$, to quantify the difference between the two optimal contests, we conduct numerical simulations across a wide range of parameterizations, including variations in ability distribution, group size, and prize budget. The simulation results are presented in Table B1 of Online Appendix B, showing that neither the winner's effort nor the total effort under the two optimal contests differ by more than 8.4%.[4]

These findings suggest that the two optimal contests are quite effective in achieving both the winner's effort and total effort goals, particularly when K is above the threshold. Even when K is below the threshold, it performs nearly as well in meeting these objectives. This means that designers can approximately achieve both goals with either optimal contest for any K. The following proposition summarizes the equilibrium properties under these two optimal contests.

Proposition 2 *(i) Both optimal contests induce full participation in equilibrium, and contestants exert effort according to*

$$e^D(t) = \begin{cases} 0 & if\ t < t^{*D} \\ \big((V + NK)F(t)^{N-1} - K\big) - \int_{t^{*D}}^{t} \big((V + NK)F(s)^{N-1} - K\big)\, ds & if\ t \geq t^{*D} \end{cases} \tag{4}$$

(ii) Both optimal contests generate more effort when the liability is higher.

For part (i), the equilibrium in the optimal contest features full participation, where every contestant with an ability lower than t^{*^D} enters and bids zero, hoping that everyone else has an ability lower than t^{*^D} so that they can equally share the prize. Although they could potentially end up with a negative prize, their expected prize is zero, making them indifferent between participating and not participating. On the other hand, a contestant with an ability higher than t^{*^D} exerts more effort as his ability increases and enjoys strictly positive payoffs. For part (ii), the reason is that whatever is feasible under a certain liability is also feasible with a higher liability, and the designer can certainly achieve higher effort levels.

3 Experimental Design

In our experimental design, we choose the ability t to be uniformly distributed on the interval $[1, 2]$. We set the number of contestants to $N = 3$ and the total prize budget to $V = 120$. As a result,

[4] An ad-hoc power calculation suggests that we need around 500 independent observations per treatment to detect this difference at the 5% significance level and with the moderate 50% power.

we have $F(t) = t - 1$, $J^T(t) = 2t - 2$, $J^W(t) = \frac{4}{3}t^3 - 3t^2 + 2t - \frac{2}{3}$, ${t^*}^T = \left(\frac{3K}{120+3K}\right)^{\frac{1}{2}} + 1$ and ${t^*}^W = max\left\{1.45, \left(\frac{3K}{120+3K}\right)^{\frac{1}{2}} + 1\right\}$. The parameters for the two optimal contests then become

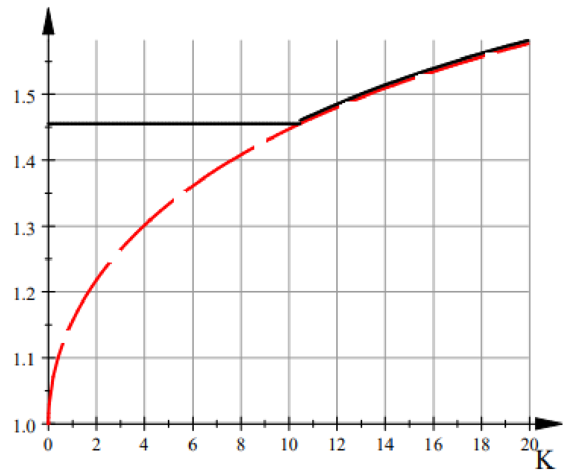
$$
\begin{aligned}
{\hat{e}^*}^D &= (120 + 2K)\,{t^*}^D - (6K + 240)\,{t^*}^{D2} + (3K + 120)\,{t^*}^{D3} \\
E^D &= K \\
S^D &= \frac{K}{\left({t^*}^D - 1\right)^2}
\end{aligned}
$$

The entry fee E^D is always equal to the liability K. In the experimental part, we primarily refer to the entry fee, but it should be understood that the entry fee and liability have the same value. Figure 1 illustrates how the cutoff ability, cutoff effort and equally shared prize change as a function of the liability K. It is worth noting that the cutoff effort decreases in K for the contest that maximizes the winner's effort when K is smaller than 10.5. This is because the cutoff ability is fixed in this case. Therefore, when K increases, the expected prize decreases for the same cutoff ability, leading to the optimal contest requiring a lower effort threshold. Also note that the shared prize can be interpreted as follows: the entry fee is refunded, and a portion of the prize budget is evenly distributed among the participants. In general, the shared prize may or may not exhaust the entire prize budget. For example, as shown in panel (c), on one hand, the shared prize consistently uses the full amount of the prize allocated for the total effort maximizing contest, which totals $120/3 + K$. On the other hand, the shared prize only uses a proportion of that amount when K is less than 10.5 for the winner's effort maximizing contest.

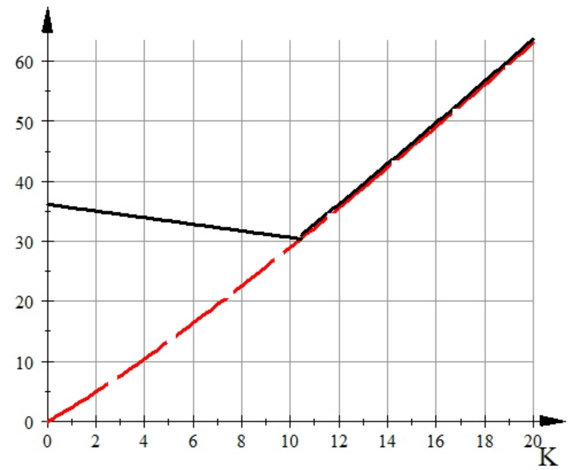
In our between-subject experiment, we compare the performance of optimal contests in six different treatments that vary the liability K and objectives. These treatments are labeled as High_TW, Medium_TW, Low_W, Low_T, Zero_W and Zero_T, where T and W indicate whether the contest can theoretically achieve the objective of maximizing the total effort or the winner's effort, respectively. In treatments High_TW and Medium_TW, the optimal contests are designed to simultaneously maximize the winner's effort and total effort. We choose a high liability of 40 (with a corresponding entry fee of 40, cutoff effort of 136.5, and equally shared prize of 80) and a medium liability of 10.5 (with a corresponding entry fee of 10.5, cutoff effort of 30.5, and equally shared prize of 50.5). The medium liability, as shown in Figure 1, is the lowest value that allows the same contest to achieve the dual objectives of maximizing both total effort and winner's effort. The high liability is expected to result in significantly higher total effort and winner's effort compared to the medium liability.

The treatments with zero liability serve as benchmarks and represent situations where the negative prize is not allowed. As shown in Figure 1, the optimal contests are different under the two objectives. In the Zero_W treatment, the cutoff effort is set to 36.5 and the equally shared prize is set to 0, allowing this contest to theoretically maximize the winner's effort (but not the total

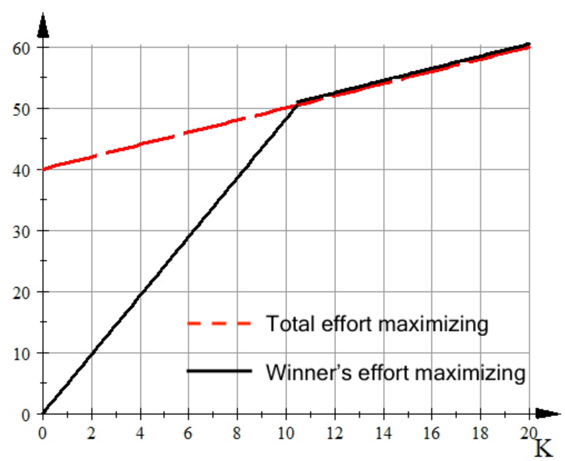
Figure 1: The effect of liability (entry fee) on the optimal contests



(a) Cutoff ability



(b) Cutoff effort



(c) Shared prize

Notes: The red dashed lines in the figure represent the parameters as a function of the liability K under the optimal contest that maximizes the total effort and the black solid lines represent the parameters under the optimal contest that maximizes the winner's effort. The two lines intersect at $K = 10.5$. This means that when $K \geq 10.5$, the same contest achieves both objectives. In subfigure (c), when $K = 0$, the equally shared prize of 40 represented by the red line becomes irrelevant for the optimal contest that maximizes the total effort, as efforts cannot be negative. In this case, a standard all-pay auction with no reserve and no entry fee maximizes the total effort.

Table 1: Experimental Design

Treatments	Entry Fee	Cutoff Effort	Cutoff Ability	Shared Prize	Expected Winner's Effort	Expected Total Effort	Matching Group	Subjects
High_TW	40	136.5	1.707	80	166.1	210	6	72
Medium_TW	10.5	30.5	1.455	50.5	133.6	192.5	6	72
Low_W	2	35.5	1.455	10	116.7	176.2	6	72
Low_T	2	4.5	1.218	42	115.6	182.9	6	72
Zero_W	0	36.5	1.455	0	113.7	172.3	6	72
Zero_T	0	0	0	N/A*	112	180	6	72

Notes: * In the Zero_T treatment, the shared prize is actually irrelevant since efforts cannot be lower than the cutoff effort of 0.

effort) under zero liability. In the Zero_T treatment, the cutoff effort is set to 0 and the equally shared prize is set to 40, enabling this contest to theoretically maximize the total effort (but not the winner's effort) under zero liability. It is important to note that the equally shared prize of 40 in Zero_T is irrelevant, as efforts cannot be strictly lower than the cutoff of 0. Therefore, the contest effectively becomes a standard all-pay auction with no reserve and no entry fee.

Finally, we recognize that the two zero liability treatments are not structurally identical due to the effective absence of the shared prize in Zero_T, which might undermine its comparability to the first two treatments with non-zero negative prizes. Therefore, we also design two treatments with low liability where the negative prize is allowed but its absolute value remains low compared to the threshold of 10.5. This means that these two contests with low liability cannot simultaneously maximize the winner's effort and total effort. Specifically, in both contests, the negative size is set to 2. In the Low_W treatment, the cutoff effort is 35.5 and the equally shared prize is 10; this contest can theoretically maximize the winner's effort (but not the total effort). In comparison, in the Low_T treatment, the cutoff effort is 4.5 and the equally shared prize is 42; this contest can theoretically maximize the total effort (but not the winner's effort). Table 1 summarizes the design for each treatment, along with the expected winner's effort and total effort associated with each treatment.

In each experimental session, there were 2 matching groups, with 12 participants in each group. At the beginning of each round, participants within a matching group were randomly assigned into 4 contests, with each contest consisting of 3 players. In each round, each participant received an endowment of 300 points, which could be used to cover the entry fee or effort cost in the contest.[5] Participants first decided whether to enter a contest to compete against other group members to win prizes. In treatments with positive entry fees, the value of the total prize depended on the number of group members who chose to enter. Participants were informed that the total prize consisted of two components: (i) a base prize of 120 points and (ii) the total amount of entry fees collected from all contestants. However, they did not know the exact number of group members choosing to enter or the exact value of the total prize until the end of the round. Participants

[5]However, participants could still incur a loss if they chose a very high effort. This only occurred once in the entire dataset.

were incentivized to predict the number of contestants in their group (including themselves) with a correct guess awarded with 10 points.

If a participant chose not to enter the contest, he had no further decisions to make in that round. If he chose to enter, he had to pay the entry fee and decide how much effort to exert in the contest. The effort cost was equal to the effort divided by the participant's privately-known ability parameter, which was independently drawn from a uniform distribution with a range of [1.00, 2.00]. Therefore, a participant's effort cost was inversely related to his ability. Each participant was privately informed about his ability parameter at the beginning of each round, and its value was redrawn for each round. To minimize the influence of different ability parameter draws on behavior, we generated one sequence of this parameter for one session, consisting of 24 participants interacting for 20 rounds. This same sequence was used in all sessions across all treatments. At the end of each round, participants were informed about the actual number of contestants, the winner's effort, and their earnings. Final earnings were determined by randomly drawing five out of the 20 rounds.

We conducted a total of 18 computerized sessions at the Economics Experimental Laboratory of the Nanjing Audit University in March 2022 and April 2024. The experiment was implemented using zTree (Fischbacher, 2007). We recruited 432 subjects from the undergraduate student population at the university. The average payment for participating in the experiment was approximately 80 RMB (approximately 12 USD), which included a 15 RMB show-up fee for a 1.5 hour experiment.[6] Upon arrival, participants were randomly assigned to computer terminals partitioned from each other. They were provided with written instructions for the experiment and the experimenter also read the instructions aloud at the beginning of each session. Participants completed a comprehension quiz to ensure they understood the instructions before proceeding. Approximately 25 minutes were dedicated to ensuring participant comprehension in each session. At the end of the experiment, participants completed a short survey that covered their demographics, attitudes toward risk and competitiveness, and the standard cognitive reflection test. Online Appendix C presents all experimental instructions.

4 Results

Our main focus is to compare the winner's effort and total effort across all treatments (Section 4.1). We also present results on the frequency of entering the contest and effort choices (Section 4.2), as well as individual-level analyses of entry and effort choices (Section 4.3).

[6]The average per-hour earnings in the experiment was substantially higher than the minimum hourly wage which is about 15-20 RMB in the local region.

4.1 Winner's effort and total effort

Figure 2a shows the average winner's effort across treatments. The quantitative prediction of the winner's effort level in each treatment is remarkably accurate. Consistent with our predictions, we observe the highest level of winner's effort in High_TW, followed by Medium_TW. The winner's effort in High_TW is significantly higher than in any other treatment ($p = 0.002$ in all five comparisons, Wilcoxon ranksum test).[7] Compared to Zero_W, High_TW boosts the winner's effort by 45.8%. Medium_TW increases the winner's effort by 15.3% relative to Zero_W, but the effect is not significant ($p = 0.240$). Also as predicted, the winner's effort levels are similar between Low_W and Low_T ($p = 0.699$) and between Zero_W and Zero_T ($p = 0.818$).

The overall pattern of total effort closely mirrors that of the winner's effort. Figure 2b displays the average total effort across all treatments. Compared to the baseline treatment Zero_T, High_TW increases the total effort by 48.5% ($p = 0.004$). Medium_TW increases the total effort by 15.5% relative to Zero_T, but the effect is not significant ($p = 0.132$). There is little difference in the total effort between Low_W and Low_T ($p = 1.000$) and between Zero_W and Zero_T ($p = 0.699$). Notably, Figure 2b also shows some differences between the observed and predicted levels of total effort. While the observed level is higher than the predicted one in High_TW ($p = 0.028$, Wilcoxon signed-rank test), the direction is reversed but the difference is not significant in any of the other treatments.

To provide further statistical evidence, we report a random effects regression analysis of the treatment effects on the winner's effort and total effort, respectively, as shown in Table B2 of Online Appendix B. The estimates and post-estimation tests are consistent with the non-parametric test results. Additionally, we observe a significantly negative round effect, indicating that both the winner's effort and the total effort tend to decrease over round, especially during the first 10 rounds (also see Figure B2 and Figure B3 in Online Appendix B for the evolution of the winner's effort and total effort, respectively). To test for robustness, we only include observations from the last 10 rounds in columns (2) and (4) of Table B2. The advantage of High_TW over the other treatments, although slightly narrower, remains highly significant.[8]

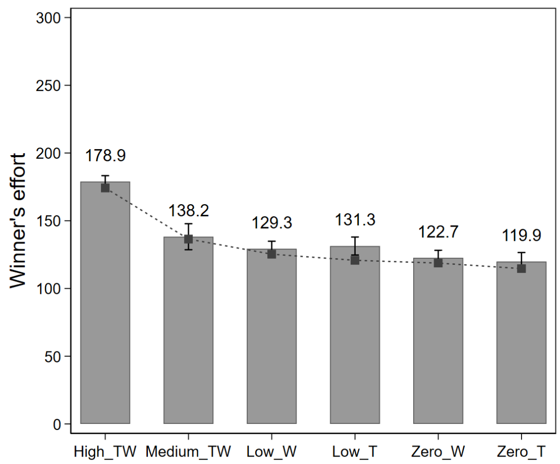
To gain a clearer understanding of the variation in effort level within each treatment, Figure 2c and Figure 2d plot the empirical CDFs of the winner's effort and total effort, respectively, across treatments. We observe that the winner's effort (and similarly, the total effort) in High_TW almost first-order stochastically dominates that in any other treatment, except for a slightly higher fraction of zero effort in High_TW.[9] This observation aligns with the theoretical prediction that a higher cutoff ability leads to a higher likelihood that all three contestants' abilities are below that cutoff

[7] Unless otherwise stated, we treat the average for each matching group as one independent observation.

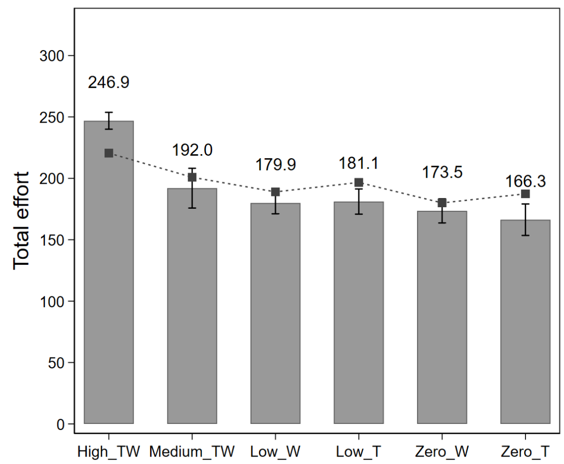
[8] For a visual presentation, Figure B1 in Online Appendix B shows the aggregated effort levels for the last 10 rounds.

[9] We test the difference in the fraction of zero effort between High_TW and all other treatments combined, finding marginally significant effects for both total effort and winner's effort ($p = 0.068$, Wilcoxon ranksum test, treating each matching group as an independent observation).

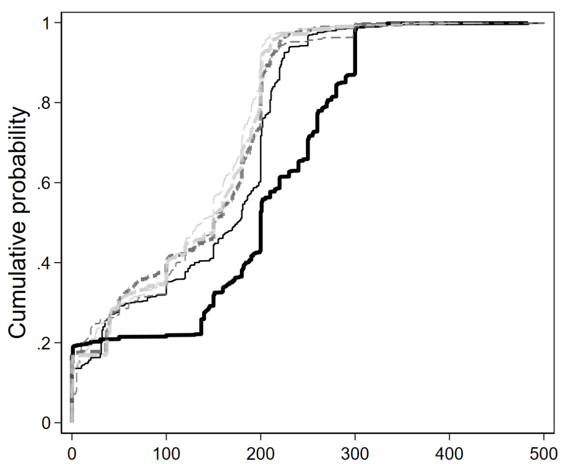
Figure 2: Averages and distributions of winner's effort and total effort



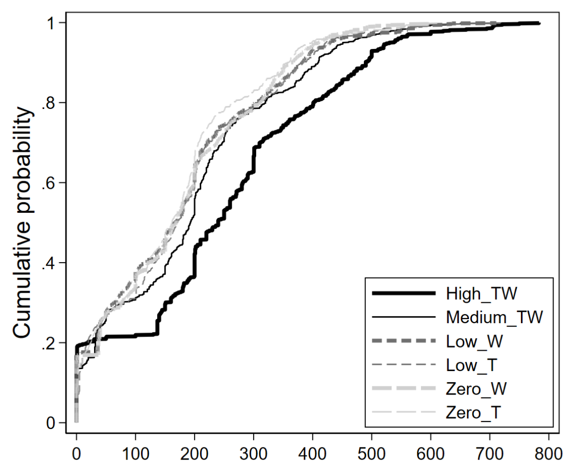
(a) Winner's effort - average



(b) Total effort - average



(c) Winner's effort - CDF



(d) Total effort - CDF

Notes: Standard errors clustered at the matching group level are indicated by bars. For average efforts on the top panel, the connected line represents the theoretical prediction in each treatment, which is derived from each individual's optimal effort function evaluated at their actual ability parameter in each group and in each round. Note that this is different from the theoretical prediction based on the expected composition of group members with heterogeneous abilities, as shown in Table 1. The predicted winner's effort is 174.2, 136.5, 125.3, 120.8, 118.8 and 114.7 in High_TW, Medium_TW, Low_W, Low_T, Zero_W and Zero_T, respectively. The predicted total effort is 220.5, 200.9, 189.0, 196.7, 180.0 and 187.4, respectively. For both winner's effort and total effort, the average in High_TW is significantly higher than in any other treatment.

value. Consequently, all contestants are expected to provide zero effort and split the base prize. Additionally, we observe kinks in the CDF at approximately the cutoff effort of 136.5, as well as at the two integers 200 and 300 in High_TW. This suggests that contestants sometimes bunch their effort choices around these natural focal points.[10]

Result 1 *The aggregated results provide supporting evidence for the key strength of our contest mechanism: it achieves the joint objective of maximizing the winner's effort and total effort throughout the whole range of liability level, with the observed effort levels closely matching the predicted ones in each treatment.*

4.2 Entry and effort choices

The previous subsection has demonstrated that the empirical patterns of the winner's effort and total effort align with the theoretical predictions. In this subsection, we test additional theoretical predictions about behavior at the individual level. The theory predicts that every player should enter the contest. In addition, those with an ability parameter below the cutoff value should enter but exert zero effort, while those with an ability parameter above the cutoff value should exert higher efforts than the cutoff effort. The positive values of cutoff ability and cutoff effort are determined by the optimal mechanism and therefore, differ across treatments, as shown in Table 1.

Table 2 presents summary statistics for entry and effort choices across all treatments.[11] First, we observe that the prediction of full entry is not supported in any treatment. The entry rate is 56.5% in High_TW, which is significantly lower than that in any other treatment (vs. Medium_TW, $p = 0.037$; vs. Low_W, $p = 0.009$; vs. Low_T, $p = 0.004$, vs. Zero_W, $p = 0.065$; vs. Zero_T, $p = 0.002$, Wilcoxon ranksum test). Figure B6 in Online Appendix B shows that the entry rate is largely stable over round in each treatment. When comparing individuals with high and low ability (determined by being above and below the cutoff ability in each treatment, as shown in Table 1), we find that high-ability individuals have a significantly higher entry rate than low-ability individuals within each treatment ($p = 0.002$ in each comparison except in Low_W where $p = 0.015$). Notably, when comparing across treatments, the entry rate for high-ability individuals is over 90% in High_TW and significantly higher than that in any other treatment except for Low_W ($p < 0.009$ in each comparison except in Low_W where $p = 0.119$). This suggests that the low entry rate in High_TW is mainly driven by low-ability individuals, who should be weakly better off by entering the contest (given that other group members play their equilibrium strategy). By contrast, high-ability individuals behave mostly consistent with the theory regarding the entry decision, especially in High_TW.

[10] Figure B4 and Figure B5 in Online Appendix B plot the observed CDFs of the winner's effort and total effort, respectively, against the predicted CDFs for each treatment. The predicted CDF is derived from each individual's optimal effort function, evaluated at their actual ability parameter in each group and in each round. In general, the observed CDFs track the predicted ones reasonably well, especially for the total effort.

[11] For robustness check, we calculate the statistics using data only from last 10 rounds in Table B3 of Online Appendix B, which shows largely similar results.

Table 2: Summary statistics for entry and effort choices

	High_TW	Medium_TW	Low_W	Low_T	Zero_W	Zero_T
Entry rate						
All	56.5%	63.7%	71.5%	72.6%	63.9%	75.2%
High ability	91.0%	76.3%	83.1%	77.9%	77.3%	/
Low ability	41.2%	46.7%	55.9%	49.1%	45.8%	/
Above-cutoff rate if enter						
All	66.5%	69.6%	60.5%	78.5%	71.1%	100%
High ability	86.6%	82.3%	74.3%	81.5%	81.7%	/
Low ability	46.6%	41.6%	32.7%	57.3%	46.8%	/
Positive effort but below-cutoff rate if enter						
All	10.0%	9.0%	5.0%	3.9%	1.8%	0%
High ability	6.2%	6.2%	4.5%	3.1%	1.7%	/
Low ability	13.7%	15.4%	5.8%	9.9%	2.1%	/
Zero effort rate if enter						
All	23.6%	21.4%	34.6%	17.6%	27.1%	24.7%
High ability	7.2%	11.6%	21.2%	15.4%	16.6%	/
Low ability	39.8%	43.0%	61.4%	32.8%	51.1%	/
Average effort if enter						
All	145.6	100.4	83.8	83.2	90.5	73.7
High ability	192.9	127.3	110.1	92.2	112.2	/
Low ability	98.9	40.9	31.0	21.2	73.7	/

Notes: High (low) ability is determined by whether a contestant's ability parameter is above (below) the cutoff value in a round. This cutoff value is 1.218 in Low_T, 1.455 in Medium_TW, Low_W and Zero_W, and 1.707 in High_TW. "Above-cutoff rate if enter" refers to the frequency of contestants' efforts above the cutoff effort, which is 36.5 in Zero_W, 35.5 in Low_W, 4.5 in Low_T, 30.5 in Medium_TW and 136.5 in High_TW.

Second, we observe that, in each treatment, high-ability individuals are significantly more likely to exert effort above the cutoff effort conditional on entry compared to low-ability individuals ($p = 0.002$ in each comparison, Wilcoxon ranksum test). This is directionally consistent with the theory, but the absolute frequency does not align as closely with the theory. According to the theory, high-ability individuals should always exert effort above the cutoff, while low-ability individuals should always exert zero effort. It is worth noting that exerting effort strictly below the cutoff and above zero is a dominated strategy for both high- and low-ability contestants. But as shown in Table 2, only a small fraction chose this strategy upon entry.[12]

Third, Figure 3a plots the average effort (unconditional on entry) categorized by finer levels of

[12] Across all treatments, the frequency of playing the dominated strategy does not significantly differ by gender, risk attitude, competitiveness, cognitive sophistication, or across different rounds.

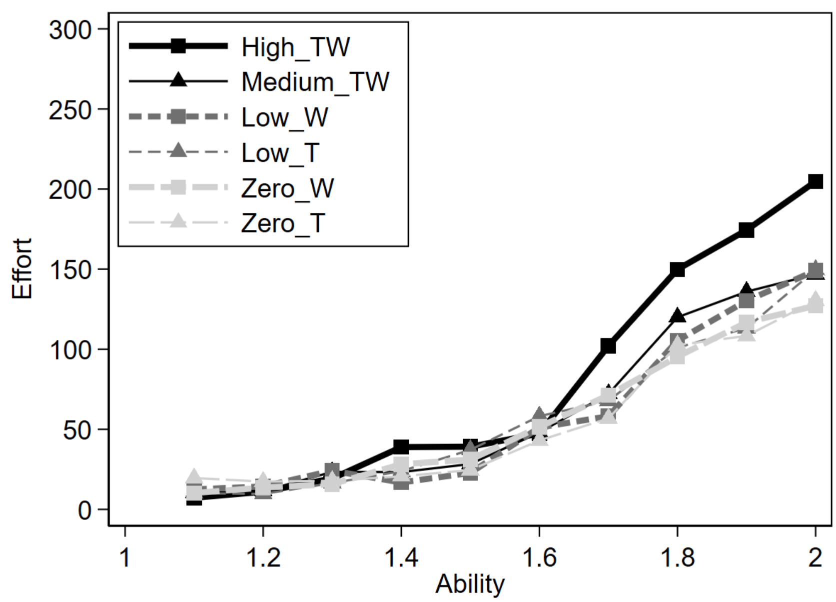
the ability parameter. When the ability parameter is below 1.6, the average effort is very similar across all treatments. However, when the ability parameter is above 1.6 (which is close to the cutoff ability of 1.707 in High_TW), the average effort is noticeably higher in High_TW than in any other treatment.[13] This finding suggests that High_TW generates the highest winner's effort primarily through the behavior of high-ability contestants.

Finally, Figure 4 compares the observed and predicted effort, sorted by ability, for each treatment. Overall, we observe that low-ability individuals tend to exert too much effort, while high-ability individuals tend to exert too little effort. This pattern of deviation appears to be most pronounced in High_TW. Interestingly, in our experiment, these two tendencies exactly balance out, resulting in the winner's effort at an average level that is remarkably close to the predicted level. Focusing on High_TW, we observe a sharp increase in effort around an ability level of 1.6, indicating a significant change in behavior as abilities approach the cutoff ability. To further investigate the relationship between contestants' ability and their behavior, Figure B7 in Online Appendix B classifies individual behavior into four categories: no entry, zero effort upon entry, effort strictly above zero and below the cutoff (i.e., dominated strategy), and finally effort above the cutoff. We primarily focus on High_TW, but for completeness, we also report the categorization for other treatments. First, individuals with abilities close to the cutoff ability (1.707) from below (i.e., low-ability individuals) entered the contest at a much lower rate compared to those with abilities above the cutoff ability (i.e., high-ability individuals). Indeed, individuals with abilities within the intervals (1.5, 1.6], (1.6,1.7] and (1.7, 1.8] chose not to enter the contest in 59.4%, 29.9% and 14.5% of the cases, respectively. Second, as abilities approach the cutoff ability, the frequency of exerting effort above the cutoff effort also increases dramatically, aligning with the decreased entry rate. Third, the frequency of playing the dominated strategy of exerting effort below the cutoff accounts for around 3.2% of all observations, indicating that our participants generally did not employ the strictly dominated strategy.

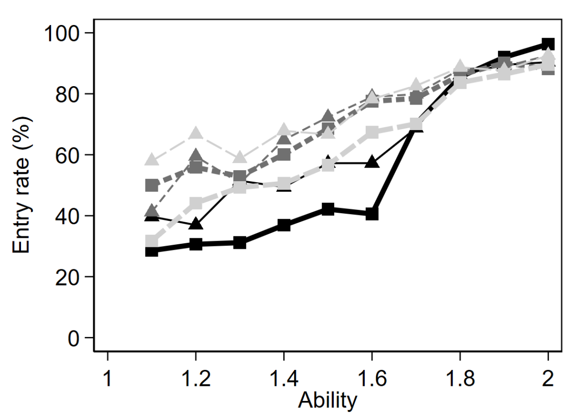
Result 2 *While High_TW produces the highest winner's effort and total effort as predicted by the theory, contestants do not always enter the contest and do not always choose the optimal effort level. This is particularly evident for low-ability individuals when the entry fee is high. They enter the contest less frequently than they should in equilibrium and when they do enter, they exert effort above the cutoff effort more often than they should. On the other hand, high-ability individuals enter the contest in over 90% of the cases with a high entry fee, and they exert significantly more effort compared to when the entry fee is low or zero (although not as much as predicted by the theory). As a result, the high entry fee (coupled with a high cutoff effort) drives up the winner's*

[13] Figure 3b and Figure 3c provide an even more detailed view of the behavior. Figure 3b displays the average entry rate across different ability levels. It shows that, given a specific ability level, low-ability individuals entered the contest less frequently in High_TW compared to any other treatment. However, the entry rate for high-ability individuals was similar across all treatments. Figure 3c plots the average effort conditional on entry across different ability levels. It reveals that, given a specific ability level, individuals exerted more effort in High_TW than in any other treatment almost across the board. Therefore, in High_TW, the higher effort exerted by low-ability individuals was offset by their lower frequency of entering the contest. On the other hand, high-ability individuals not only exerted more effort but entered the contest as frequently as in any other treatment.

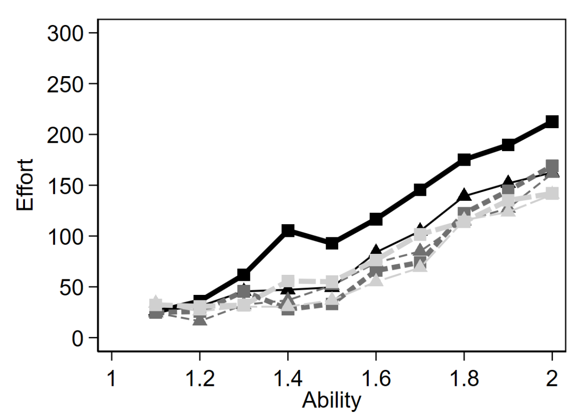
Figure 3: Effort and entry rate by ability



(a) Average effort



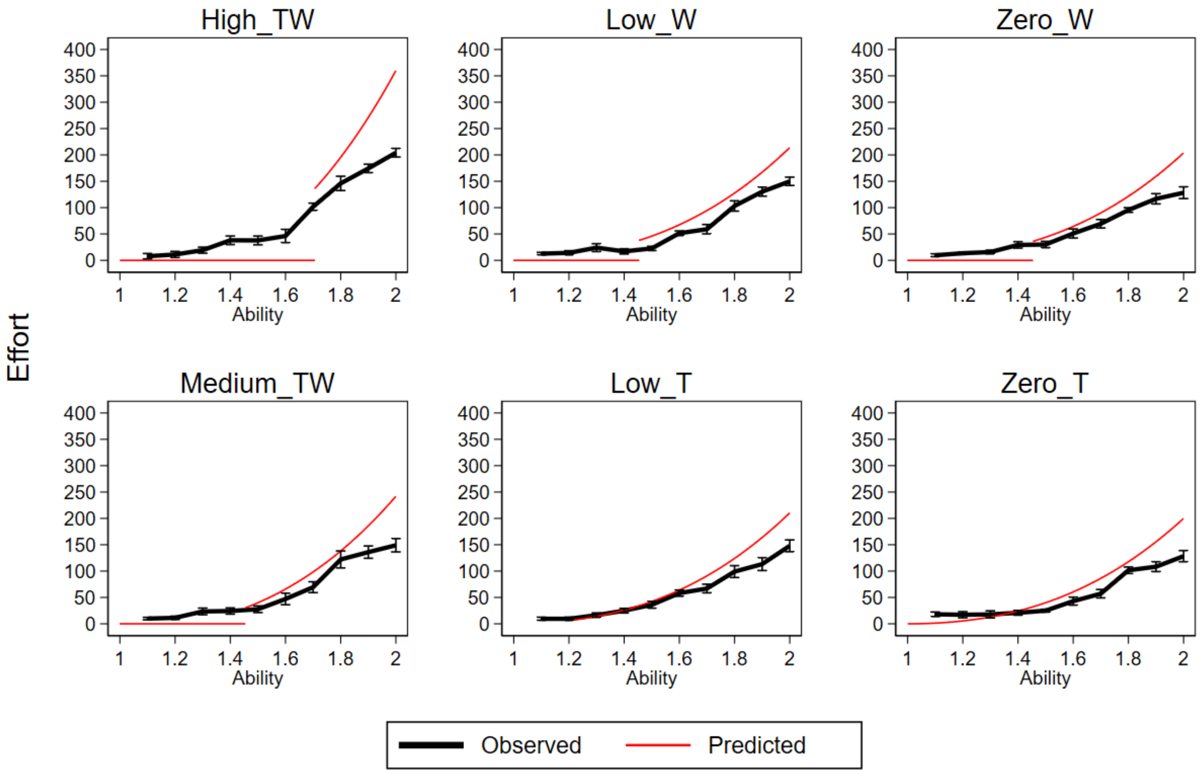
(b) Entry rate



(c) Effort conditional on entry

Notes: The ability parameter is categorized into ten groups: [1, 1.1], (1.1, 1.2], . . . , (1.9, 2]. In the figure, we use the upper bound to indicate each group.

Figure 4: Observed and predicted effort by ability



Notes: The ability parameter is categorized into ten groups: [1, 1.1], (1.1, 1.2], ..., (1.9, 2]. In the figure, we use the upper bound to indicate each group. Standard errors clustered at the matching group level are indicated by bars.

effort primarily through the behavior of high-ability contestants.

4.3 Individual-level results

Next, we turn to individual-level analyses to investigate how individuals decide to enter the contest, and if so, how they choose their effort. Table 3 presents the results from random effects regressions for the entry and effort choices. The regressions include treatment indicators and control variables such as a contestant's ability parameter in a given round, his belief about the number of entrants (excluding himself), and individual characteristics collected from the post-experimental questionnaire.[14] We report the estimates separately for all rounds and for the last 10 rounds. However, since the results are similar, we will focus on the results using the full sample in the following discussion.

[14] In each round, participants were asked to guess the total number of entrants, including themselves. Since this belief measure is correlated with their own entry decision, we impute the belief about the number of other entrants by subtracting the count of own entry from the original belief measure. We use this adjusted belief measure in the data analysis.

Table 3: Random effects regressions for entry and effort choices

	All rounds		Last 10 rounds	
	Pr(Entry)	Effort if enter	Pr(Entry)	Effort if enter
High_TW	-0.262***	61.466***	-0.405***	65.319***
	(0.036)	(7.388)	(0.045)	(9.900)
Medium_TW	-0.164***	22.452***	-0.232***	23.546***
	(0.040)	(8.174)	(0.044)	(8.668)
Low_W	-0.067	9.230	-0.081	9.468
	(0.075)	(6.274)	(0.075)	(7.927)
Low_T	-0.061	7.438	-0.099*	2.440
	(0.044)	(6.301)	(0.051)	(8.845)
Zero_W	-0.177***	13.108*	-0.195***	12.513
	(0.043)	(7.937)	(0.059)	(9.444)
Ability	0.627***	157.808***	0.642***	160.096***
	(0.030)	(7.361)	(0.035)	(7.514)
Believe 1 enters	-0.067***	34.997***	-0.090***	32.254***
	(0.022)	(5.532)	(0.019)	(7.770)
Believe 2 enter	-0.285***	42.139***	-0.336***	42.866***
	(0.028)	(6.093)	(0.030)	(8.084)
Female	-0.012	7.016	-0.044	4.356
	(0.034)	(5.186)	(0.040)	(5.175)
Risk	0.032**	0.135	0.036***	0.490
	(0.012)	(2.337)	(0.014)	(2.754)
Competitive	0.019*	-0.466	0.023**	-0.767
	(0.010)	(2.144)	(0.011)	(2.112)
CRT	0.036***	-2.733	0.034***	-0.628
	(0.012)	(2.519)	(0.012)	(2.674)
Round	-0.001	-1.597***	0.001	-1.353***
	(0.002)	(0.223)	(0.002)	(0.466)
Clusters	36	36	36	36
N	8640	5810	4320	2927

Notes: Columns (1) and (3) report the average marginal effects from random effects probit regressions on the entry decision. Columns (2) and (4) report estimates from random effects linear regression on the effort choice for contestants who have entered the contest. Standard errors clustered at the matching group level are in parentheses. Zero_T serves as the benchmark. "Risk" is self-reported general attitudes toward risk-taking in daily life on the scale from 1 (not risk-taking at all) to 7 (extremely risk-taking). "Competitive" is self-reported general attitudes toward being competitive in daily life on the scale from 1 (not competitive at all) to 7 (extremely competitive). "CRT" refers to the Cognitive Reflection Test using the standard three questions developed by Frederick (2005) to assess cognitive ability. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Consistent with the descriptive statistics, the results from the regression analysis show that the high entry fee induces the lowest entry rate but the highest effort level conditional on entry. As expected, individuals with higher ability are more likely to enter the contest and exert more effort conditional on entry. The beliefs about the number of other entrants play an important role: the more individuals expect others to enter the contest, the less likely they are to enter themselves, they exert more effort conditional on entry. This finding is intuitive, as more intense competition reduces the likelihood of winning the prize, thus reducing the incentive to enter. However, once individuals have made the decision to enter, they tend to bid harder to increase their chances of winning.[15] In Table B5 of Online Appendix B, we conduct a series of similar regressions separately for each treatment. We find that the estimated effects of ability level and belief are largely consistent across all treatments, although individual behavior in High_TW appears to be more sensitive toward ability and belief than in other treatments.[16] In Section 5.2, we will further show that high-ability players' beliefs about the intensity of competition can fully explain their underprovision of effort conditional on entry.

Finally, we find that individual attitudes toward risk and competitiveness, as well as cognitive sophistication, are associated with entry choices. Specifically, individuals who are more risk-seeking, more competitive, or cognitively more sophisticated are more likely to enter the contest. However, Table B5 shows that these factors are not consistently significant across all treatments. Risk attitudes are significant in High_TW, Medium_TW and Low_W; competitiveness is significant in High_TW; and cognitive sophistication is significant in Zero_W and Zero_T. Given the variation in the effects of these individual characteristics across treatments, we refrain from drawing definitive conclusions based on these findings. Importantly, we conclude that these individual characteristics cannot fully explain the superior performance of our optimal mechanism compared to the baseline treatment.

5 Possible explanations for deviations in individual behavior

In this section, we provide further discussion on some important deviations in individual behavior from the theoretical predictions, especially in High_TW. The findings from the High_TW treatment suggest that while the aggregated outcomes are remarkably close to the theoretical predictions, individual behavior deviates from the theory in important ways. In particular, low-ability participants often chose not to enter the contest, although the optimal mechanism is designed to induce full participation. Furthermore, high-ability participants provided too little effort upon entry. Subsection

[15] This finding is consistent with Boosey, Brookins and Ryvkin (2020) who studied an experimental contest with endogenous entry. They found that when the exact number of other entrants was disclosed, individuals were less likely to enter the contest if the number of competitors was larger. To further validate this finding, we also conduct a robustness analysis by adding explanatory variables of whether an individual entered in the previous round and the number of other entrants in their own group in the previous round. The regression results reported in Table B4 of Online Appendix B show that while an individual's previous entrance significantly predicts their entry decision in the current round, the number of other entrants in the previous round significantly predicts effort conditional on entry. However, the effect sizes of these variables are considerably smaller compared to beliefs.

[16] Since the optimal effort function is not smooth over ability in the optimal mechanism, we also estimate the regression separately for high- and low-ability individuals in each treatment except Zero_T (see Table B6 and Table B7 in Online Appendix B respectively). In High_TW, the estimates suggest that the entry decisions of high-ability individuals are not sensitive to their ability, which is not surprising given that over 90% of them chose to enter, as shown in Table 2. By contrast, the entry decisions of low-ability individuals are more sensitive to their ability, and this higher sensitivity is also observed in their effort choices upon entry. However, in Medium_TW and Zero_W, the pattern is somewhat reversed: both the entry and effort choices of high-ability individuals appear to be more sensitive to their ability than those of low-ability individuals.

5.1 discusses potential explanations for the non-entry of low-ability players. Subsection 5.2 provides an explanation for the underprovision of effort of high-ability players, utilizing an additional treatment in which all players are forced to enter the contest.

5.1 Non-entry of low-ability players

One major deviation is that low-ability players often choose not to enter the contest. The following proposition shows that non-entry can be rationalized by risk aversion. The proof is presented in Online Appendix A.

Proposition 3 *For the contest $(E, \hat{e}, S)$ under risk aversion, consider an equilibrium with the following structure. There exist two cutoffs t_1 and t_2 with $\underline{t} < t_1 < t_2 < \bar{t}$. Players with $t \in [\underline{t}, t_1]$ do not enter, players with $t \in (t_1, t_2]$ enter and put in zero effort; players with $t \in (t_2, \bar{t}]$ enter and put in effort according to the same strictly increasing funciton. Consider the following two nonlinear equations:*

$$u(0) = F(t_2)^{N-1} u(S-E) + \left(1 - F(t_2)^{N-1}\right) u(-E)$$

$$F(t_2)^{N-1} u(S-E) = \sum_{m=0}^{N-1} C_{N-1}^{m} F(t_1)^{n-1-m} \left(F(t_2) - F(t_1)\right)^m u(V + mE) - \frac{\hat{e}}{t_2}$$

If the solutions of t_1 and t_2 from the two nonlinear equations are interior, i.e., $\underline{t} < t_1 < t_2 < \bar{t}$, then this is the equilibrium.

In the above equilibrium, contestants with ability lower than t_1 do not enter. In particular, in our High_TW treatment, such an equilibrium arises when contestants exhibit certain CRRA utlity function. Further, this equilibrium reduces to the equilibrium in our main result when contestants are risk neutral. Our experimental data provide consistent evidence on the role of risk aversion. Table B7 in Online Appendix B shows that, among low-ability individuals, more risk seeking types are more likely to enter the contest in High_TW.

Further, a non-equilibrium-based explanation is that the behavior of non-entrants is empirically optimal, as entering the contest would only reduce their actual payoff. To test this possibility, we conduct additional data analysis by allowing non-entrants to counterfactually make the theoretically optimal choice by entering the contest and providing zero effort. We then compare their counterfactual payoff to their actual payoff. The result shows that in High_TW low-ability non-entrants would indeed have been worse off if they had chosen to enter, with average payoff decreasing from 300 to 288.5. The next subsection will provide further supporting evidence for this explanation.

In summary, it appears that both risk aversion and non-entrance being empirically optimal can explain low-ability players' tendency to not enter the contest. Having said that, we do not suggest these are the only possible channels. For instance, another possibility is loss aversion, as even though entering is optimal in equilibrium, a loss-averse low-ability contestant may still choose to opt out of the contest due to the potential psychological cost of losing. Fully characterizing the impact of loss aversion on behavior in our contests is challenging. Our mechanism design approach is not directly applicable to a model that incorporates additional behavioral assumptions about individual preferences, such as loss aversion. While there is limited existing research exploring the role of loss aversion in contests (Gill and Stone, 2010; Dato, Grunewald and Müller, 2018; Fu et al., 2022), Boosey, Brookins and Ryvkin (2020) is, as far as we know, the only paper that incorporates loss aversion to explain individual endogenous entry into a contest. However, their contest model assumes complete information, which makes it relatively easier to derive the equilibrium impact of loss aversion on behavior. Further research is needed to fully understand the implications of loss aversion in our specific contest setting.[17]

5.2 An additional treatment with mandatory entry

Since theory anticipates full entry, it is of interest to consider how individual behavior would be shaped when participants are forced to enter. To this end, we implement another treatment, called *High_Forced*, which is identical to the High_TW treatment except that during the first 10 rounds contest entry is mandatory. The purpose of this treatment is twofold. First, we ask whether mandatory entry helps contestants to focus on their effort decisions and therefore aligns their effort choices more closely with the theoretical predictions. Second, since mandatory entry is only implemented in the first 10 rounds, we can examine whether experiencing full participation affects the voluntary entry and effort decisions in the following 10 rounds, where the game is identical to that in the High_TW treatment. We conducted three sessions with another 72 subjects from the same student pool for the High_Forced treatment in April 2024.

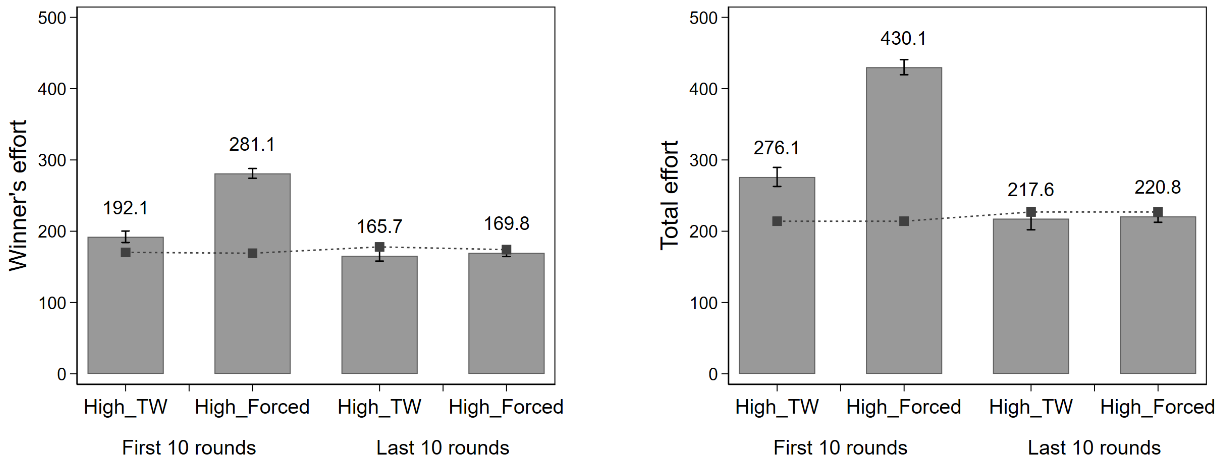
Figure 5 shows the average winner's effort and total effort for High_Forced. For the ease of comparison, we also include data from High_TW in the figure. During the first 10 rounds, compared to voluntary entry, mandatory entry substantially increases both types of effort ($p = 0.002$, Wilcoxon ranksum test), which are also much higher than predicted levels. However, during the last 10 rounds, there is virtually no difference between the two treatments when mandatory entry is removed ($p = 0.818$ for winner's effort and $p = 0.937$ for total effort). Table B8 in Online Appendix B provides complementary statistical evidence from random effects regressions.[18]

Turning to aggregated results on effort choices, as shown in Table 4, under mandatory entry, high-ability contestants exert effort above the cutoff effort (trivially conditional on entry) in 86% of

[17] Yet, another possible explanation is that, since low-ability contestants are indifferent between entering and not entering in equilibrium, we would naturally expect them to enter only half of the time in the experiment. However, Table 2 shows that in High_TW, especially during the last 10 rounds, low-ability players entered the contest less than half of the time, indicating that their behavior is not simply the result of randomness.

[18] Figure B8 and Figure B9 in Online Appendix B show the evolution of the winner's effort and total effort, respectively, for High_Forced. Both figures show a sharp drop in effort beginning from the 11th round. Figure B10a and Figure B10b plot the empirical CDFs of the winner's effort and total effort, respectively, for High_Forced. Both figures show that the CDF under mandatory entry first-order stochastically dominates that under voluntary entry. Figure B11 and Figure B12 plot the observed CDFs of the winner's effort and total effort, respectively, against the predicted CDFs for High_Forced. Both figures show that the observed CDF under mandatory entry also first-order stochastically dominates the predicted one. By contrast, when mandatory entry is removed during the last 10 rounds, the observed CDF closely tracks the predicted one.

Figure 5: Winner's effort and total effort in High_TW and High_Forced



(a) Winner's effort (b) Total effort

Notes: Standard errors clustered at the matching group level are indicated by bars. The connected line represents the theoretical prediction, which is derived from each individual's optimal effort function evaluated at their actual ability parameter in each group and in each round. Note that this is different from the theoretical prediction based on the expected composition of group members with heterogeneous abilities, as shown in Table 1. And the predicted effort can also differ between the first and last 10 rounds. The predicted winner's effort is 170.4 and 178.0 for the first and last 10 rounds, respectively. The predicted total effort is 214.1 and 227.0 for the first and last 10 rounds, respectively.

the time, which is similar to the rate of 90% under voluntary entry ($p = 0.437$, Wilcoxon ranksum test). However, low-ability contestants do so in 37% of the time, which is lower than the rate of 55% under voluntary entry ($p = 0.026$). Further, under mandatory entry, high-ability contestants exert significantly more effort (trivially conditional on entry) than their counterparts under voluntary entry ($p = 0.002$), whereas low-ability ones exert 22% less effort (97.3 versus 120, $p = 0.180$). Hence, mandatory entry appears to move effort choices of low-ability contestants somewhat closer to the theoretical prediction (i.e., always exerting zero effort). However, this effect is weak and unsustainable: when mandatory entry is removed during the last 10 rounds, low-ability contestants behave similarly under both treatments (67.6 versus 70.3). In particular, they still choose to enter the contest in only 36% of the time.[19] Meanwhile, mandatory entry encourages high-ability contestants to exert even higher effort, thereby driving up the winner's effort as well as total effort. This effect, however, is also short-lived: when mandatory entry is removed, high-ability contestants' behavior also becomes similar under both treatments. Figure B14 in Online Appendix B shows even finer details on the relationship between abilities and effort/entry choices. It provides consistent evidence that (i) the much higher winner's effort and total effort observed under mandatory entry is attributed to both the full participation and the higher effort provided by high-ability contestants;

[19] Figure B13 in Online Appendix B shows the evolution of contest entry rate for High_Forced, indicating an immediate drop in the entry rate beginning from the 11th round.

(ii) when mandatory entry is removed, the experience of forced participation in earlier rounds has almost no effect on behavior of either high- or low-ability contestants in later rounds.

Table 4: Summary statistics for entry and effort choices for High_TW and High_Forced

	High_TW	High_Forced	High_TW	High_Forced
	First 10 rounds		Last 10 rounds	
Entry rate				
All	60.0%	100%	53.1%	51.4%
High ability	90.7%	100%	91.2%	84.2%
Low ability	46.8%	100%	35.4%	36.2%
Above-cutoff rate if enter				
All	70.6%	51.2%	61.8%	57.6%
High ability	89.8%	85.6%	83.7%	83.3%
Low ability	54.7%	36.5%	35.6%	29.8%
Positive effort but below-cutoff rate if enter				
All	9.0%	4.7%	11.0%	9.2%
High ability	4.6%	0.9%	7.7%	4.7%
Low ability	12.7%	6.3%	14.9%	14.0%
Zero effort rate if enter				
All	20.4%	44.0%	27.2%	33.2%
High ability	5.6%	13.4%	8.7%	12.0%
Low ability	32.6%	57.1%	49.4%	56.2%
Average effort if enter				
All	153.4	143.4	136.7	143.2
High ability	193.6	250.7	192.3	213.3
Low ability	120.0	97.3	70.3	67.6

Notes: High (low) ability is determined by whether a contestant's ability parameter is above (below) the cutoff value of 1.707 in a round. "Above-cutoff rate if enter" refers to the frequency of contestants' efforts above the cutoff effort of 136.5.

Why does the experience of forced participation have almost no impact on low-ability individuals' behavior, especially their entry decisions, in later rounds? As the counterfactual analysis reported in subsection 5.1 suggests, all else equal, low-ability non-entrants could have been worse off if they had chosen to enter the contest. Here, we consistently find that during the first 10 rounds, average payoff of low-ability individuals under mandatory entry is significantly lower than that under voluntary entry (248.6 vs. 283.1, $p = 0.002$, Wilcoxon ranksum test). Comparing low-ability individuals' entry choices across rounds within High_Forced, their average payoff significantly increases to 299.3 during the last 10 rounds when mandatory entry is removed ($p = 0.002$). Hence, the experience of forced participation is mostly negative for low-ability players, thus leading them to stay outside of the contest in later rounds.[20]

Why do high-ability contestants exert higher effort under mandatory entry compared to voluntary entry? As it turns out, this can be explained by their belief about the number of other contestants. Under voluntary entry, high-ability players enter the contest in over 90% of the time but tend to exert effort lower than the predicted level (see Figure 4). Their behavior may be a rational response to the anticipation of a lower number of entrants than the equilibrium level. Indeed, off the equilibrium path, if one or more contestants choose not to enter the contest, the remaining entrants should exert lower effort than the level predicted on the equilibrium path. It is consistent with the evidence from subsection 4.3 that individual effort tends to be higher when they believe in a greater number of other group members having entered the contest. The comparison to mandatory entry allows us to provide further evidence. In particular, we test whether under voluntary entry those who believe that all other group members have chosen to enter the contest exert a similar level of effort compared to those under mandatory entry. Table B9 in Online Appendix B provides evidence from a regression analysis, showing that any treatment difference in effort conditional on entry is eliminated once controlling for such a belief.

Result 3 *Mandatory entry does not help align behavior more closely with the theoretical predictions, nor does the experience of mandatory entry influence behavior. However, the experimental data from the High_Forced treatment provide insights into the observed behavioral deviations. For low-ability individuals, the reason for their frequent choice not to enter the contest is that their payoff is significantly lower when forced to participate. This is consistent with the counterfactual analysis reported in subsection 5.1 and provides a complementary explanation based on risk aversion. For high-ability individuals, the tendency to exert effort below the predicted level stems from their skepticism about full participation. When we fix this belief by implementing mandatory entry, their effort levels are largely restored to the predicted levels.*

6 Conclusion

This paper introduces an optimal contest with negative prizes that can simultaneously maximize both the winner's effort and the total effort. The optimal design can be implemented by a modified all-pay auction with entry fee and reserve. In equilibrium, every contestant enters the contest, and only those with sufficiently high ability exert effort above the cutoff level, while low-ability entrants provide zero effort. We test the theoretical predictions through a laboratory experiment and find that, on average, both winner's effort and total effort closely align with the predicted levels. The observed deviations in individual behavior can be explained by risk aversion, negative experience associated with entering the contest, and players' beliefs about the intensity of competition.

[20]Under mandatory entry, low-ability contestants could have been better off if they had always provided zero effort, resulting in average payoff of 316.4, which is higher than the outside payoff of 300 (which, of course, is not an available option).

In practice, it is likely that different contestants may have different levels of liability. In many situations, such as B2B settings, the designer often possesses knowledge of contestants' heterogeneous liability levels, as they typically conduct extensive research on their customers. Suppose contestant i has liability K_i, where $K_1 > K_2 > ... > K_n$, and these values are known by the designer. It is natural to ask what the optimal contest among the structure $(E, \hat{e}, S)$ would be. If the entry fee level E is such that $K_i \geq E > K_{i+1}$, we know that only the first i contestants can afford to enter the contest. Given this, our construction of the optimal contest in Proposition 1 can be used to derive the optimal value for $\hat{e}$ and S with the modification that the number of contestants is i instead of n. As a result, the search of the optimal contest is reduced to the search of the optimal entry fee. To determine the optimal entry fee, we can, without loss of generality, restrict the analysis to a set of n options $\{K_1, K_2, \ldots, K_n\}$. This is because for any entry fee E such that $K_{i+1} < E < K_i$, the designer would benefit from choosing the optimal contest with an increased entry fee set to K_i (note that the number of entrants does not change) by Proposition 2. It is obvious that the optimal entry fee does not have to be at K_n, and can induce partial entry: for instance, when K_n is much lower than K_{n-1}, it becomes too costly to induce contestant n to participate.[21]

A practical implication of our study is that contest designers may not need to choose between maximizing the winner's effort and maximizing the total effort in a contest. Our optimal contest design suggests the possibility of achieving both objectives simultaneously, which are among the most important goals of a contest. The experimental support for this potential "killing-two-birds-with-one-stone" property provides encouraging evidence for its practical applicability and effectiveness. An important avenue for future research is to examine whether this observed property holds in contests with a larger number of participants, compared to our relatively small-scale experiment. Larger-scale contests are more likely to attract high-ability participants, but our finding that high-ability contestants exert lower-than-predicted effort raises questions about whether the objective of maximizing the winner's effort can still be achieved. At the same time, the inherently higher competitiveness of larger-scale contests could lead to increased effort levels overall. Determining which effect dominates in such settings requires further empirical investigation, and we leave this question open for future exploration.

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[21] Allowing for private liability in the model would be interesting but presents significant theoretical challenges. The difficulty lies in the fact that, without knowing contestants' liabilities, it is difficult to anticipate how many contestants can afford to enter the contest—a critical factor for constructing $(E, \hat{e}, S)$. Consequently, the designer would need to rely on contestants' self-reported liabilities. As a result, this becomes a mechanism design problem with multiple dimensional private information, a well-known theoretically hard problem. As such, this avenue is reserved for future investigation. We thank the editorial team for pointing us toward this direction and the associate editor for the insight.

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Online Appendix

A Omitted proofs

Proof for Proposition 1: To derive the optimal contest in maximizing the winner's effort, we can adapt the mechanism design approach in Liu et. al (2018). A direct mechanism is formally defined below. Let $\tilde{t}_i \in [a, b]$ be contestant i's reported ability. Given the profile of reports $\tilde{\mathbf{t}} = (\tilde{t}_1, \cdots, \tilde{t}_N)$, the contest designer gives a prize of $v_i(\tilde{\mathbf{t}})$ to contestant i and demands an effort of $e_i(\tilde{\mathbf{t}})$ from him.[22] Since the contests we consider have the feature that losers also need to pay for the effort, we restrict to a subset of direct mechanism where $e_i(\tilde{\mathbf{t}}) = e_i(\tilde{t}_i)$. Define the expected prize of contestant i with report $\tilde{t}_i$ as

$$V_i(\tilde{t}_i) = \int_{\mathbf{t}_{-i}} v_i(\tilde{t}_i, \mathbf{t}_{-i}) \mathbf{f}_{-i}(\mathbf{t}_{-i}) d\mathbf{t}_{-i}, \tag{5}$$

where $\mathbf{t}_{-i} = (t_1, \cdots, t_{i-1}, t_{i+1}, \cdots, t_N)$ and $\mathbf{f}_{-i}(\mathbf{t}_{-i})$ denotes the density of $\mathbf{t}_{-i}$.

Given that the other contestants truthfully report their abilities, contestant i's expected payoff when reporting $\tilde{t}_i$ is

$$\begin{aligned} u_i(\tilde{t}_i, t_i) &= \int_{\mathbf{t}_{-i}} v_i(\tilde{t}_i, t_{-i}) \mathbf{f}_{-i}(\mathbf{t}_{-i}) d\mathbf{t}_{-i} - \frac{e_i(\tilde{t}_i)}{t_i} \\ &= V_i(\tilde{t}_i) - \frac{e_i(\tilde{t}_i)}{t_i}. \end{aligned}$$

The contest designer's objective can be expressed as:

$$\max_{\{v_i(\cdot), e_i(\cdot), \forall i\}} R = \int_{\mathbf{t}} \left[\max_i \{e_i(t_i)\} + t_0(V - \sum_i v_i(\mathbf{t})) \right] \mathbf{f}(\mathbf{t}) d\mathbf{t} \tag{6}$$

subject to the following feasibility constraints:

$$u_i(t_i, t_i) \geq u_i(\tilde{t}_i, t_i), \forall \tilde{t}_i, t_i, \forall i, \tag{7}$$

$$u_i(t_i, t_i) \geq 0, \forall t_i, \forall i, \tag{8}$$

$$\sum_i v_i(\mathbf{t}) \leq V, \forall \mathbf{t}, \tag{9}$$

$$v_i(\mathbf{t}) \geq -K, \forall \mathbf{t}, \forall i, \tag{10}$$

$$e_i(\mathbf{t}) \geq 0, \forall \mathbf{t}, \forall i. \tag{11}$$

The feasibility constraints consist of five parts: (7) is the incentive compatibility constraint, (8) is

[22] As a contestant's payoff is linear in effort and prize, it is without loss of generality to focus on a deterministic mechanism. In fact, $v_i(\tilde{\mathbf{t}})$ and $e_i(\tilde{\mathbf{t}})$ can be interpreted as the expected prize and the expected effort.

the participation constraint, (9) is the designer's budget constraint, (10) is the lower bound imposed on prizes, and (11) is the nonnegative effort constraint.

Define $\tilde{u}_i(\tilde{t}_i, t_i) = t_i \cdot u_i(\tilde{t}_i, t_i)$. Then

$$\tilde{u}_i(\tilde{t}_i, t_i) = t_i V_i(\tilde{t}_i) - e_i(\tilde{t}_i).$$

Constraints (7) and (8) can be rewritten in terms of $\tilde{u}_i(\cdot,\cdot)$. From (7) and the Envelope Theorem, we have

$$\frac{d\tilde{u}_i(t_i, t_i)}{dt_i} = \left.\frac{\partial \tilde{u}_i(\tilde{t}_i, t_i)}{\partial t_i}\right|_{\tilde{t}_i = t_i} = V_i(t_i),$$

which leads to

$$\tilde{u}_i(t_i, t_i) - \tilde{u}_i(a, a) = \int_a^{t_i} V_i(s) ds.$$

Standard derivations such as those in Myerson (1981) lead to the following lemma. The proof is omitted here.

Lemma 1 *Mechanism $(\mathbf{v}(\cdot), \mathbf{e}(\cdot))$ is feasible if and only if the following conditions hold together with (9), (10) and (11):*

$$e_i(t_i) = t_i V_i(t_i) - \int_a^{t_i} V_i(s) ds - a \cdot u_i(a, a), \forall t_i, \forall i, \tag{12}$$

$$V_i(t_i') \geq V_i(t_i),\ \forall t_i' > t_i, \forall i, \tag{13}$$

$$u_i(a, a) \geq 0, \forall i.$$

Note that in the optimal mechanism, we must have $u_i(a, a) = 0$, i.e., the lowest ability contestant must earn zero informational rent. If $u_i(a, a) > 0$, the contest designer can simply decrease the informational rent for every ability and yield a higher level of expected total effort. Given (5) and (12), we can replace effort $\mathbf{e}(\cdot)$ by the prize function $\mathbf{v}(\cdot)$ and rewrite the contest designer's objective function as

$$\max \int_{\mathbf{t}} \sum_i \left[J^W(t_i) - t_0\right] v_i(\mathbf{t}) \mathbf{f}(\mathbf{t}) d\mathbf{t} + t_0 V. \tag{14}$$

Therefore, the contest designer's optimization problem can be restated as maximizing (14), subject to (9), (10), (11), (12) and (13). It is easy to see that, compared with Liu et. al (2018), the only difference is that the virtual ability function now is $J^W(t_i)$ instead of $J^T(t_i)$. It then follows that the contest proposed in the proposition is optimal.

When $K > \max\left\{\frac{VF(J^{T-1}(0))^{N-1}}{1-F(J^{T-1}(0))^{N-1}}, \frac{VF(J^{W-1}(0))^{N-1}}{1-F(J^{W-1}(0))^{N-1}}\right\} = \frac{VF(J^{W-1}(0))^{N-1}}{1-F(J^{W-1}(0))^{N-1}}$, we have ${t^*}^T(K) = {t^*}^W(K) = F^{-1}((\frac{NK}{V+NK})^{\frac{1}{N-1}})$, and thus the two optimal contests are the same. **Q.E.D.**

Proof for Proposition 3: Given the proposed equilibrium structure, we can calculate a player's payoff for the following actions.

No entry: $u(0)$.

Enter and bid zero: $F(t_2)^{N-1}u(S-E)+\left(1-F(t_2)^{N-1}\right)u(-E)$.

Enter and bid $\hat{e}$:

$$\sum_{m=0}^{N-1} C_{N-1}^{m} F(t_1)^{N-1-m}\left(F(t_2)-F(t_1)\right)^m u(V+mE)+\left(1-F(t_2)^{N-1}\right)u(-E)-\frac{\hat{e}}{t}. \tag{15}$$

Note that the payoff from the first two options does not depend on a player's ability. We can pin down the two cutoffs. For a player with ability t_1, he is indifferent between no entering and entering and bidding zero. We thus have

$$u(0)=F(t_2)^{N-1}u(S-E)+\left(1-F(t_2)^{N-1}\right)u(-E)$$

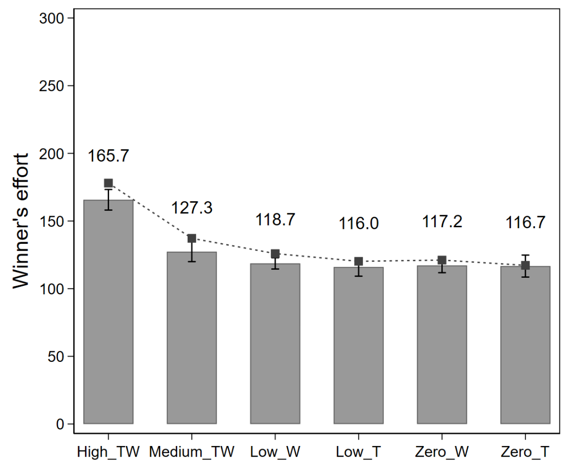
For player with ability t_2, he is indifferent between entering and bidding zero or bidding $\hat{e}$. We thus have

$$\begin{aligned}
& F(t_2)^{N-1}u(S-E)+\left(1-F(t_2)^{N-1}\right)u(-E) && (16)\\
= & \sum_{m=0}^{N-1} C_{N-1}^{m} F(t_1)^{N-1-m}\left(F(t_2)-F(t_1)\right)^m u(V+mE)+\left(1-F(t_2)^{N-1}\right)u(-E)-\frac{\hat{e}}{t_2} && \\
& F(t_2)^{N-1}u(S-E) && \\
= & \sum_{m=0}^{N-1} C_{N-1}^{m} F(t_1)^{N-1-m}\left(F(t_2)-F(t_1)\right)^m u(V+mE)-\frac{\hat{e}}{t_2} && (17)
\end{aligned}$$

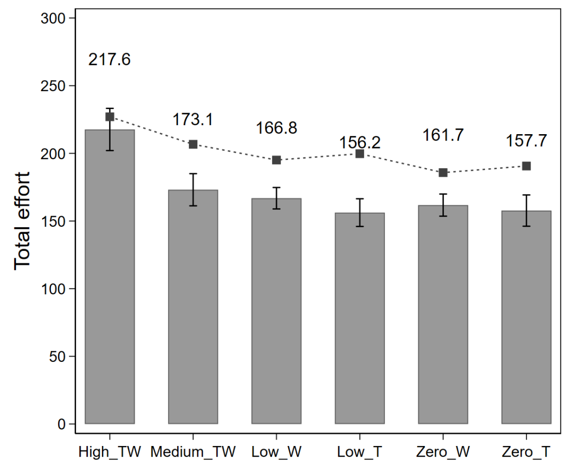
These two indifference conditions are exactly the two nonlinear equations in the proposition. If the solutions are interior, then we have verified the structure of the equilibrium. It is then routine to show that no types would have incentive to deviate given the equilibrium. **Q.E.D.**

B Additional Figures and Tables

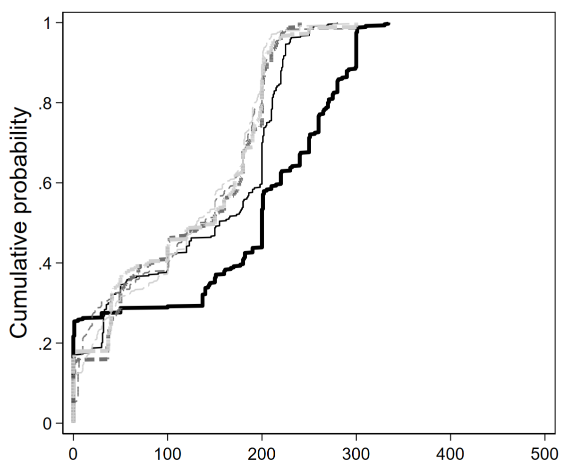
Figure B1: Averages and distributions of winner's effort and total effort during the last 10 rounds



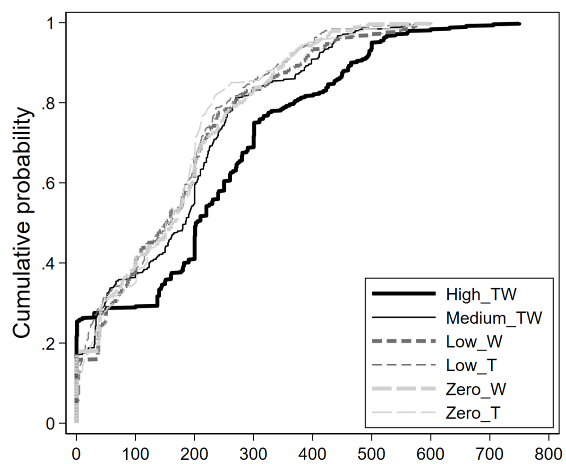
(a) Winner's effort - average



(b) Total effort - average



(c) Winner's effort - CDF



(d) Total effort - CDF

Notes: Standard errors clustered at the matching group level are indicated by bars. For average efforts on the top panel, the connected line represents the theoretical prediction in each treatment, which is derived from each individual's optimal effort function evaluated at their actual ability parameter in each group and in each round. Note that this is different from the theoretical prediction based on the expected composition of group members with heterogeneous abilities, as shown in Table 1. The predicted winner's effort is 174.2, 136.5, 125.3, 120.8, 118.8 and 114.7 in High_TW, Medium_TW, Low_W, Low_T, Zero_W and Zero_T, respectively. The predicted total effort is 220.5, 200.9, 189.0, 196.7, 180.0 and 187.4, respectively. For both winner's effort and total effort, the average in High_TW is significantly higher than in any other treatment.

Figure B2: Winner's effort over round

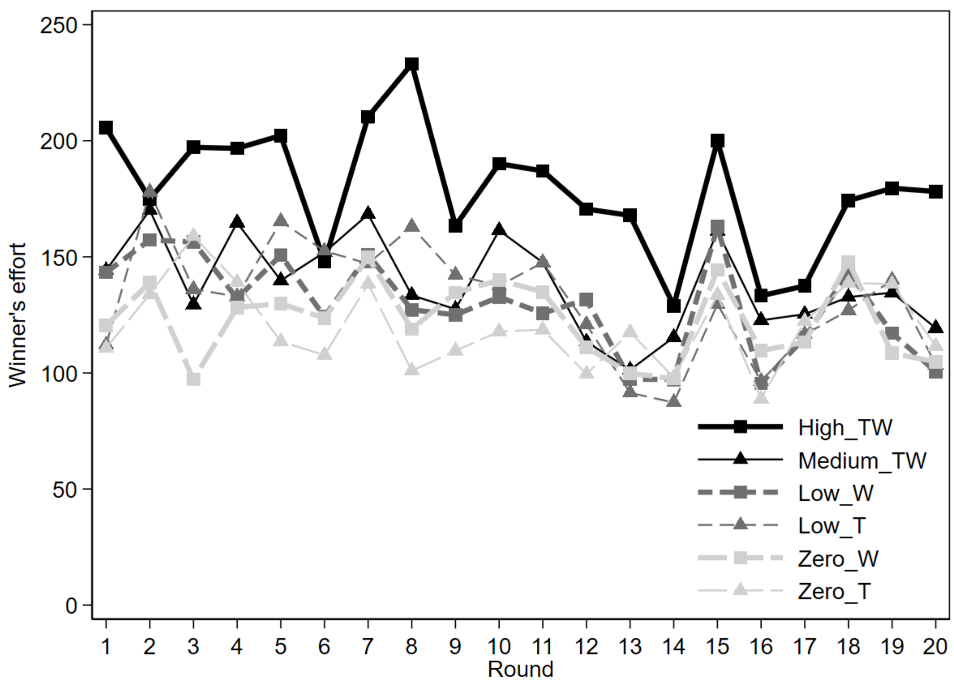


Figure B3: Total effort over round

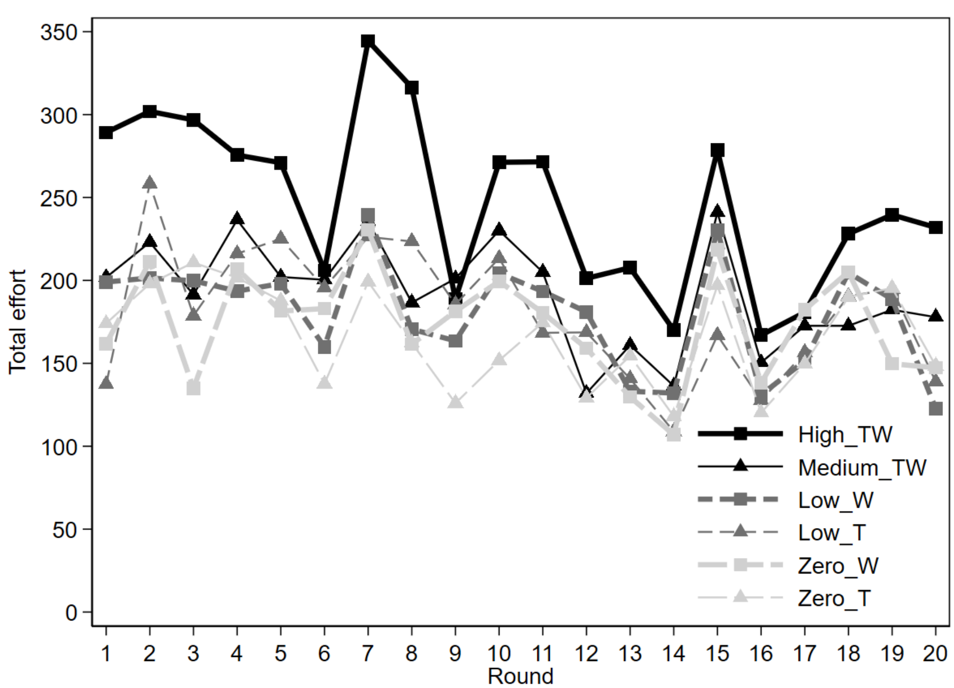


Figure B4: CDFs of observed and predicted winner's effort by treatment

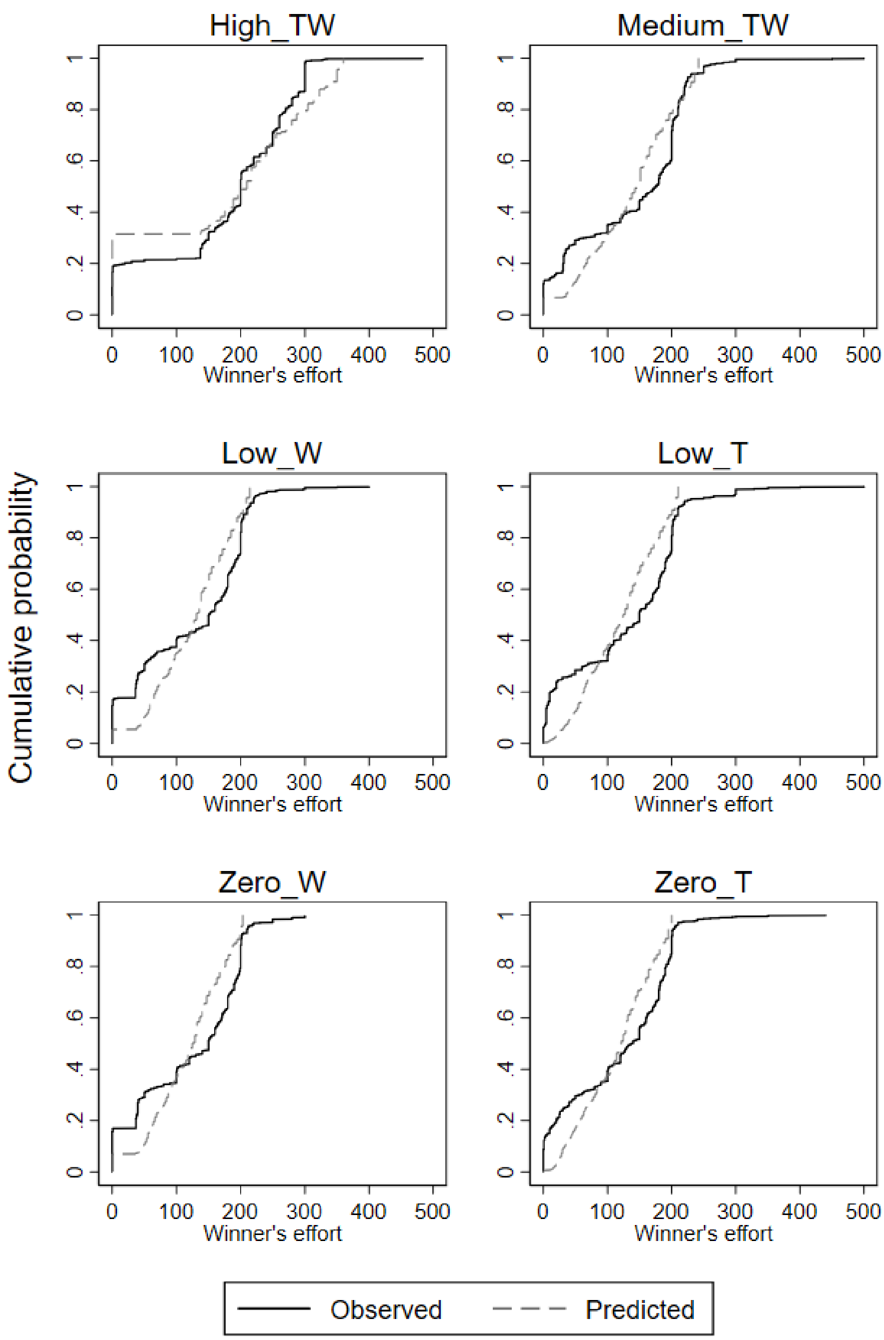


Figure B5: CDFs of observed and predicted total effort by treatment

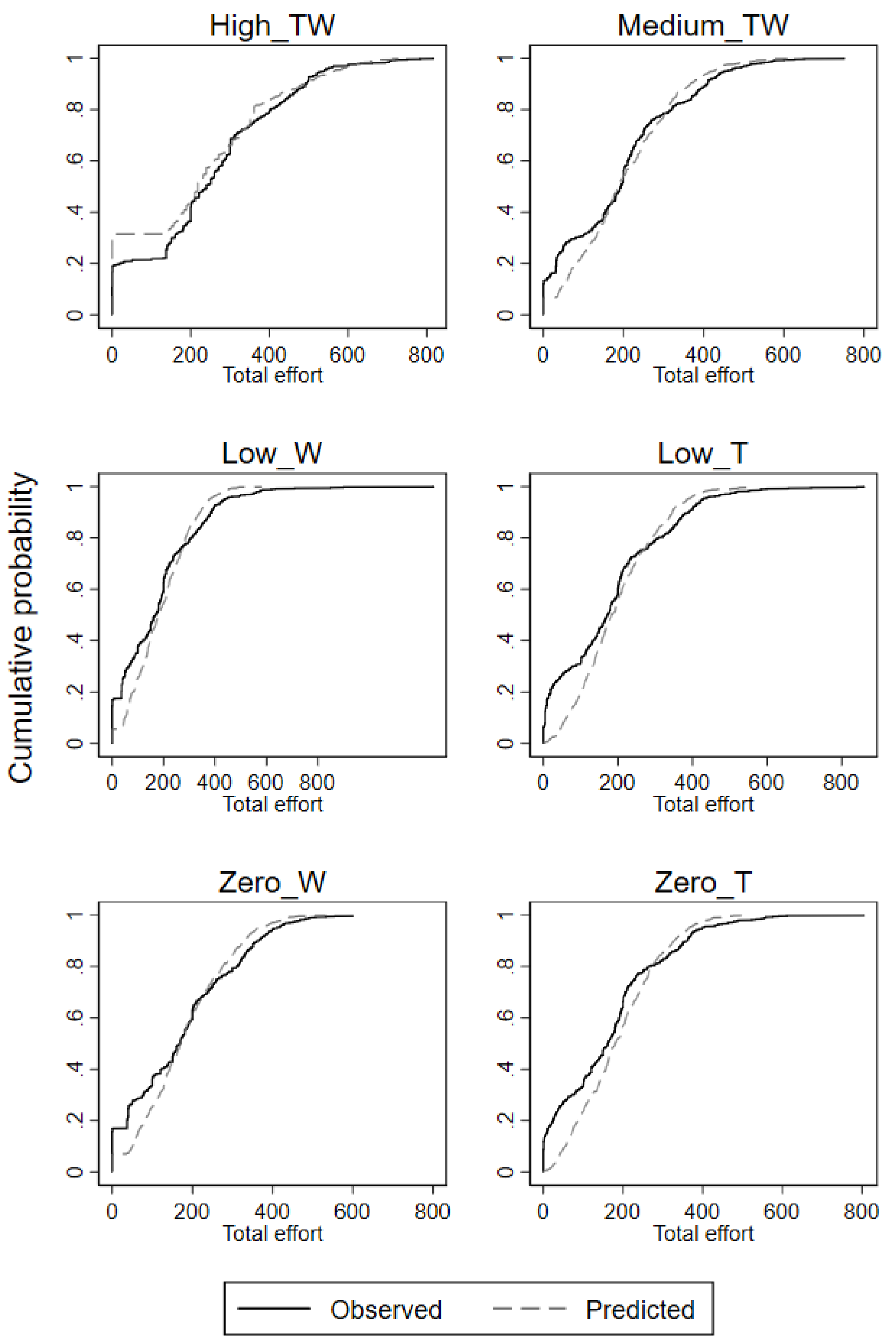


Figure B6: Frequency of entering the contest over round

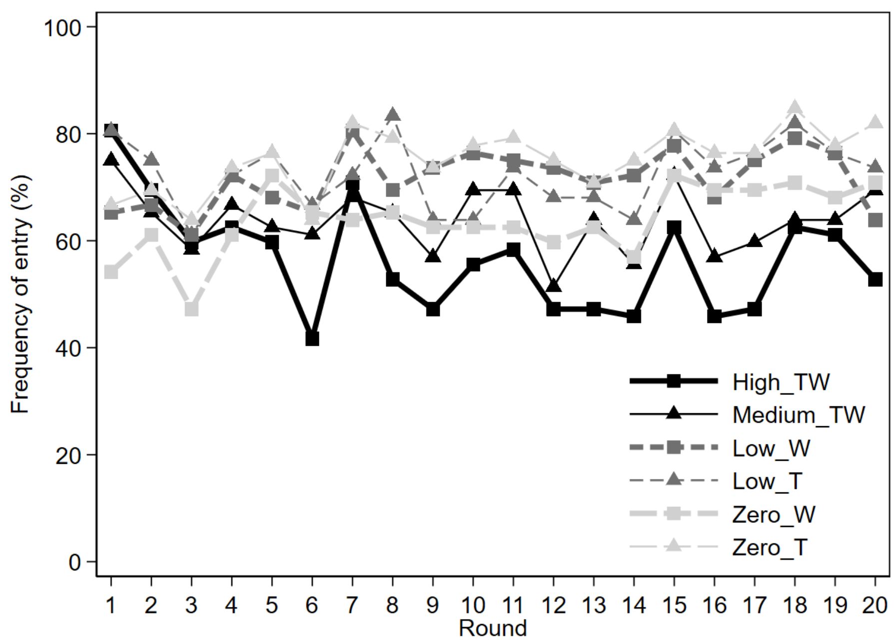
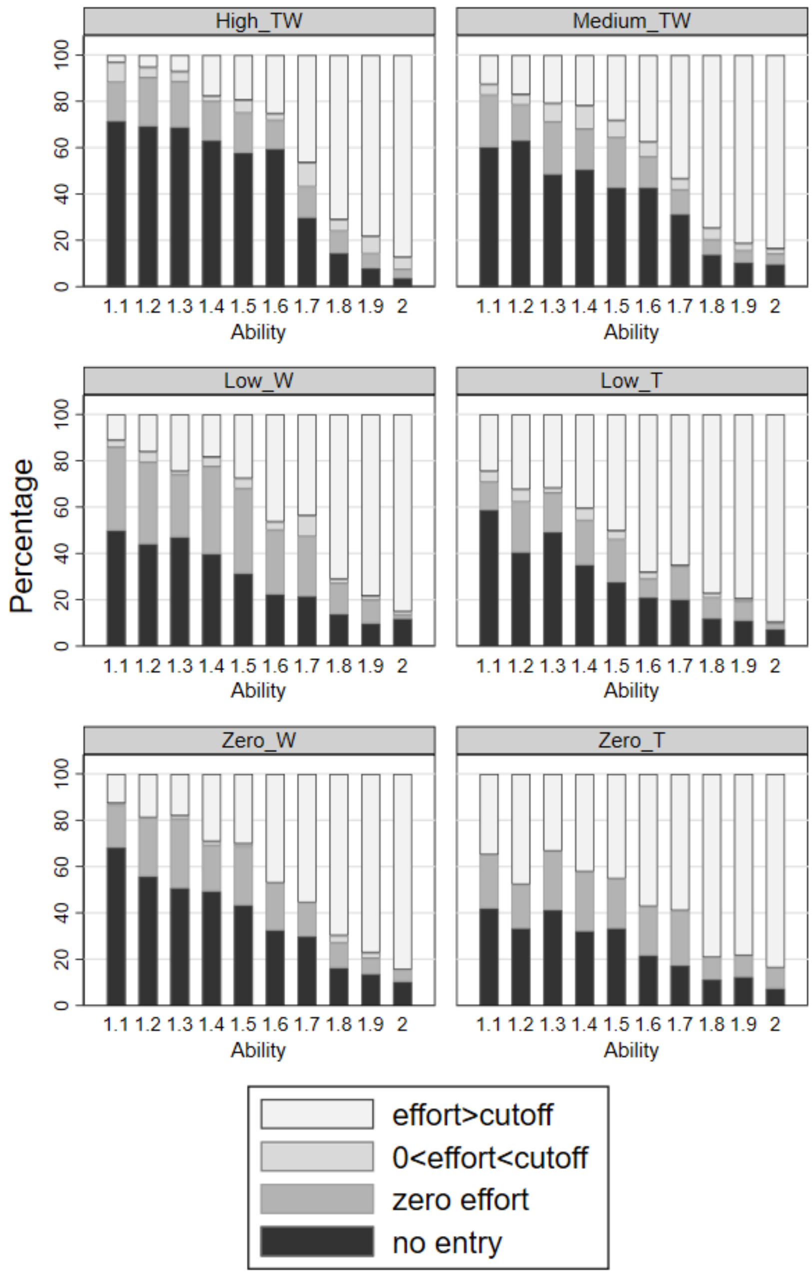


Figure B7: Categorization of behavior by ability



Notes: The ability parameter is categorized into ten groups: [1, 1.1], (1.1, 1.2], . . . , (1.9, 2]. In the figure, we use the upper bound to indicate each group.

Figure B8: Winner's effort over round in High_TW and High_Forced

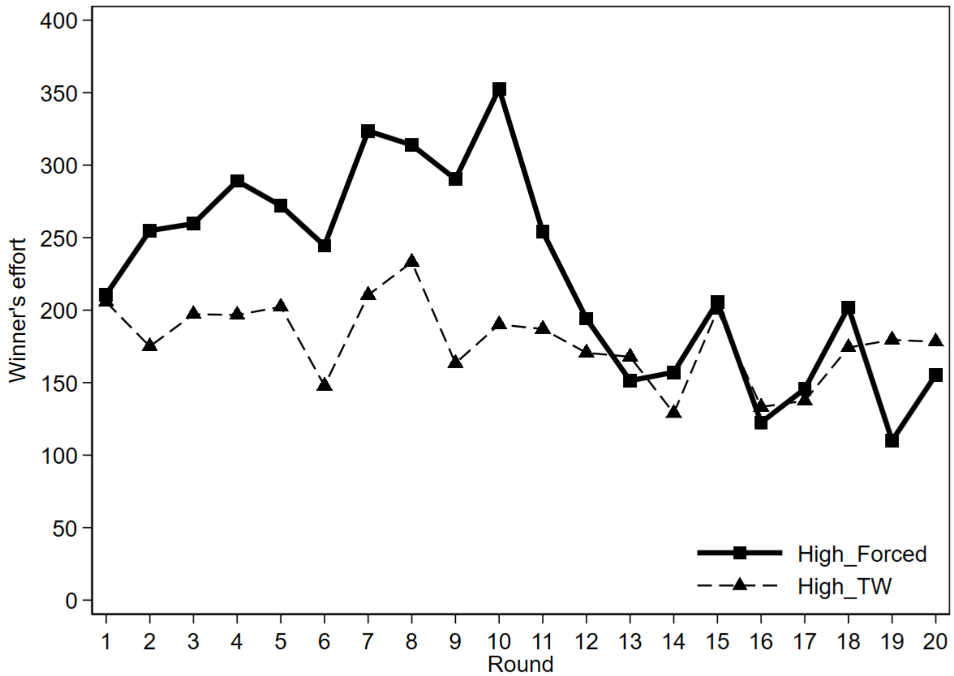


Figure B9: Total effort over round in High_TW and High_Forced

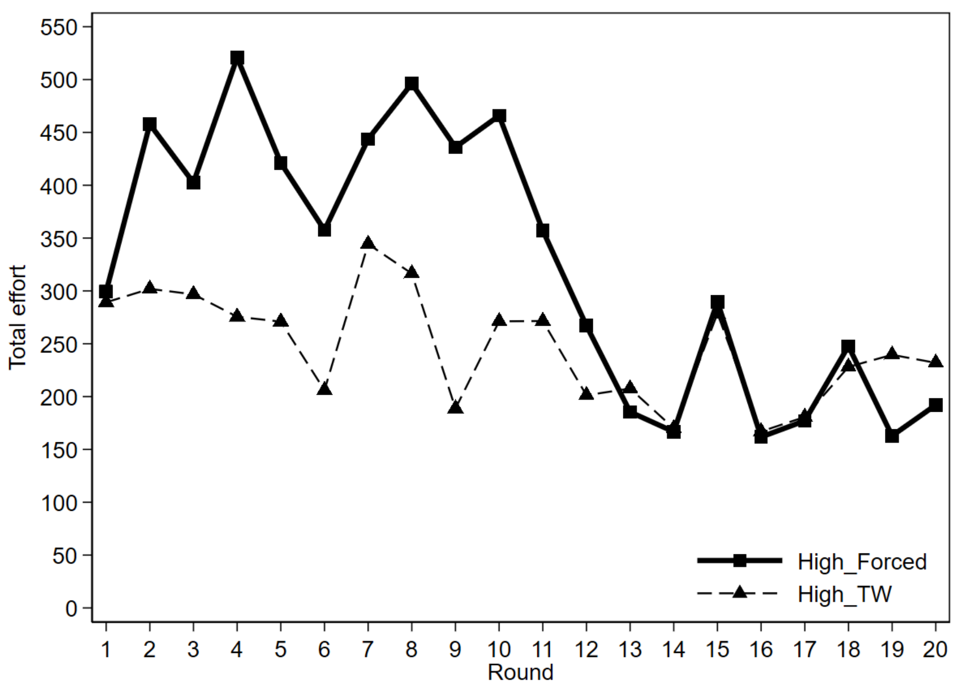
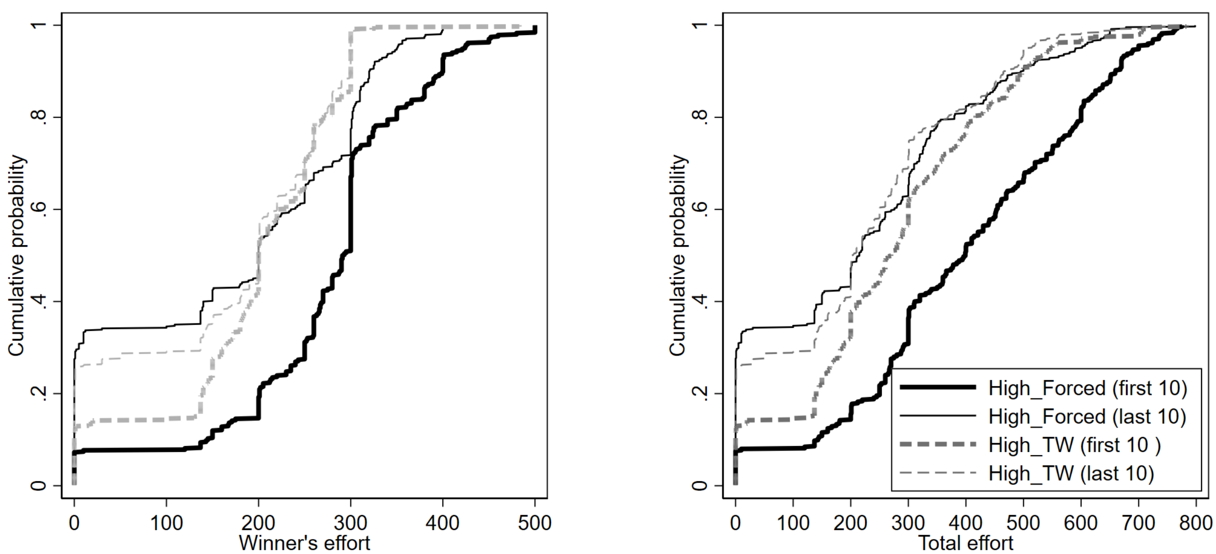


Figure B10: CDFs of winner's effort and total effort in High_TW and High_Forced



(a) Winner's effort

(b) Total effort

Figure B11: CDFs of observed and predicted winner's effort by treatment in High_TW and High_Forced

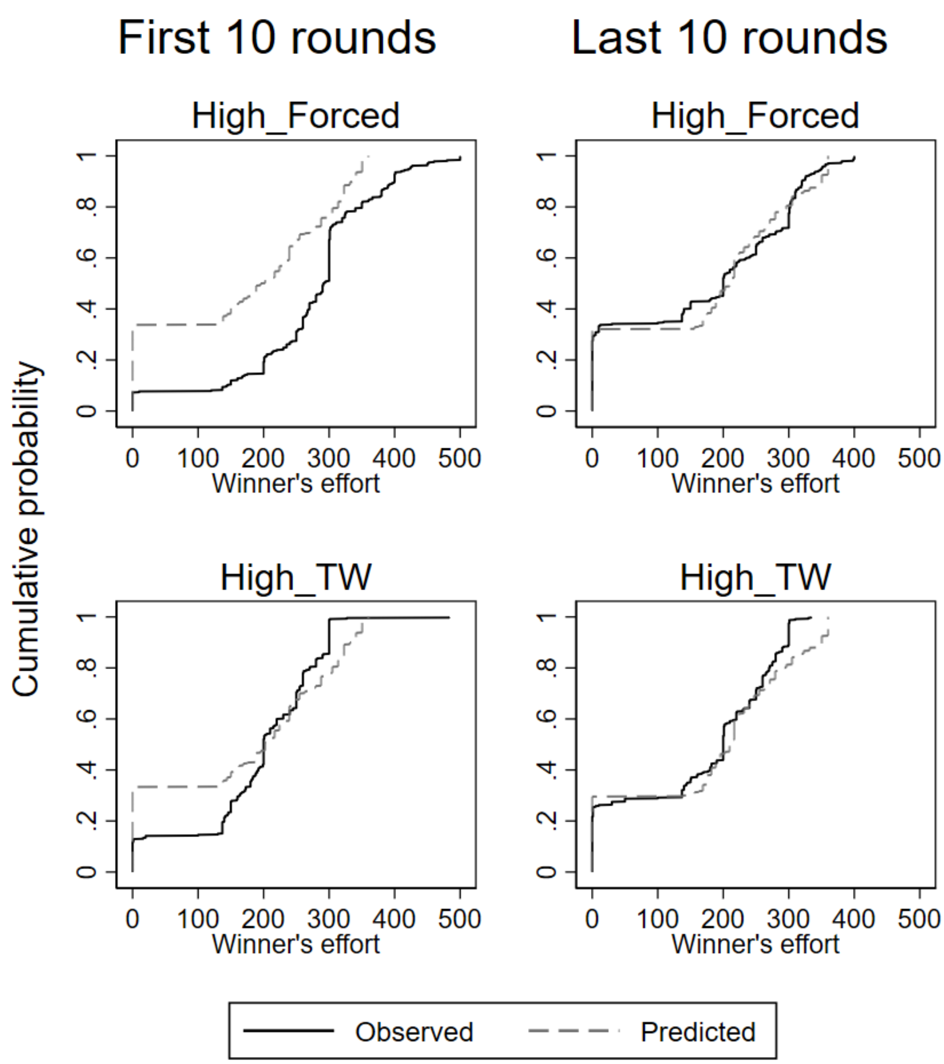


Figure B12: CDFs of observed and predicted total effort by treatment in High_TW and High_Forced

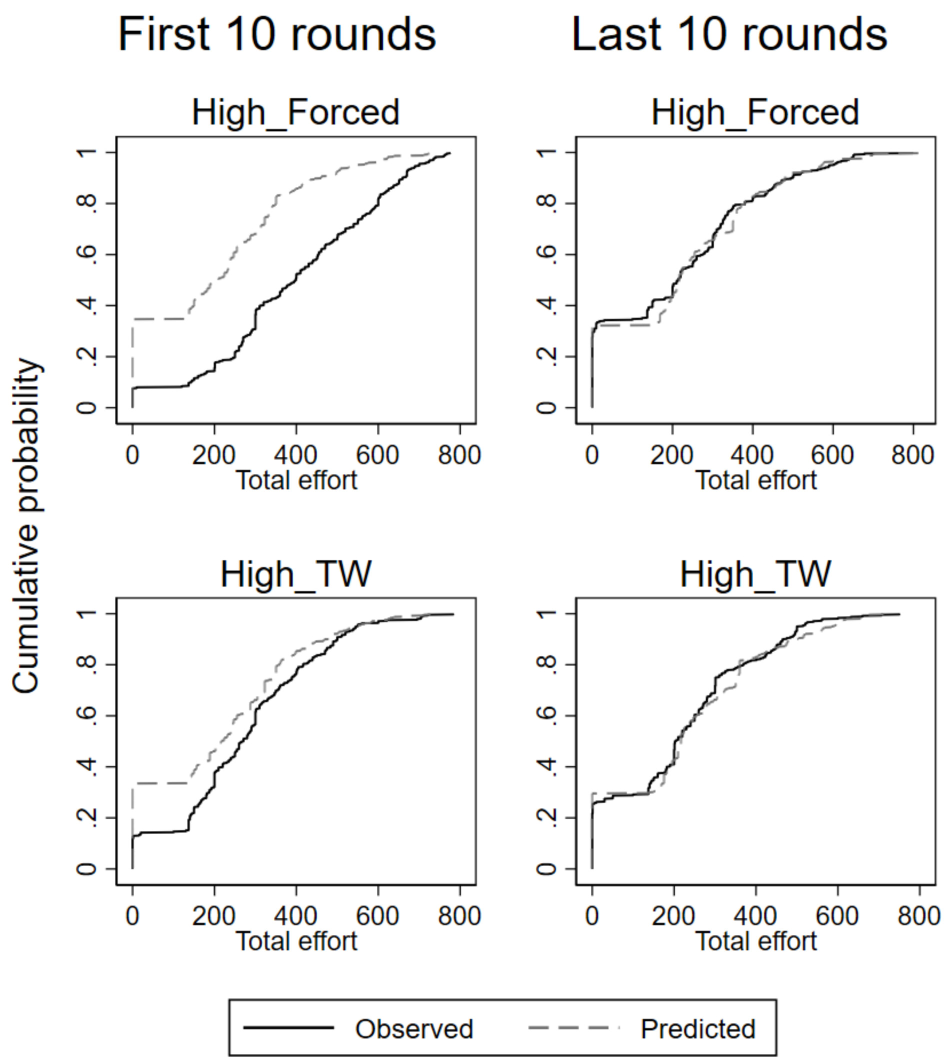


Figure B13: Frequency of entering the contest over round in High_TW and High_Forced

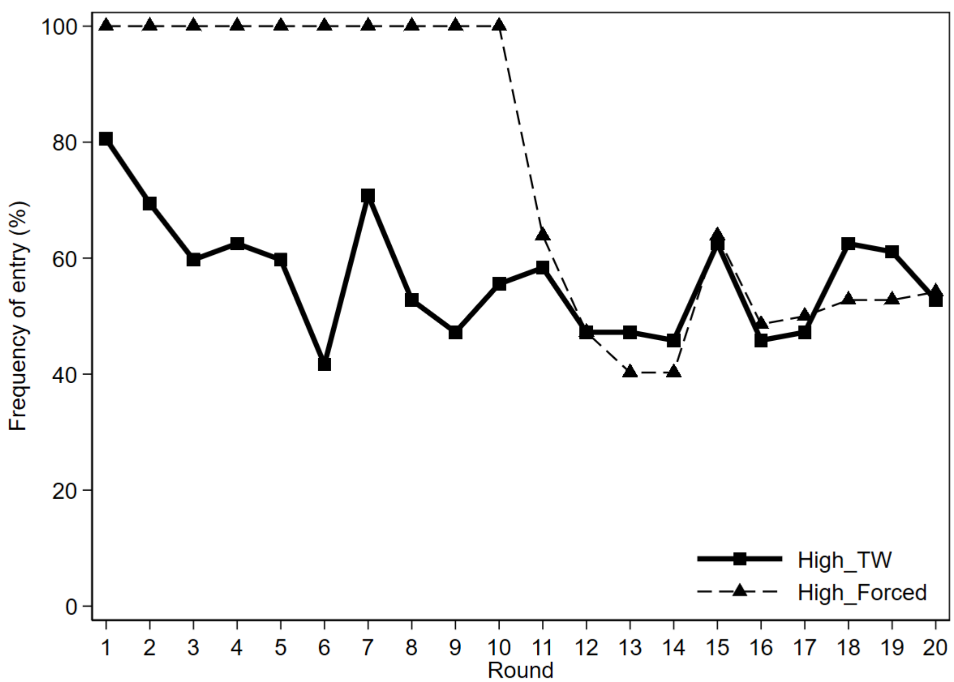
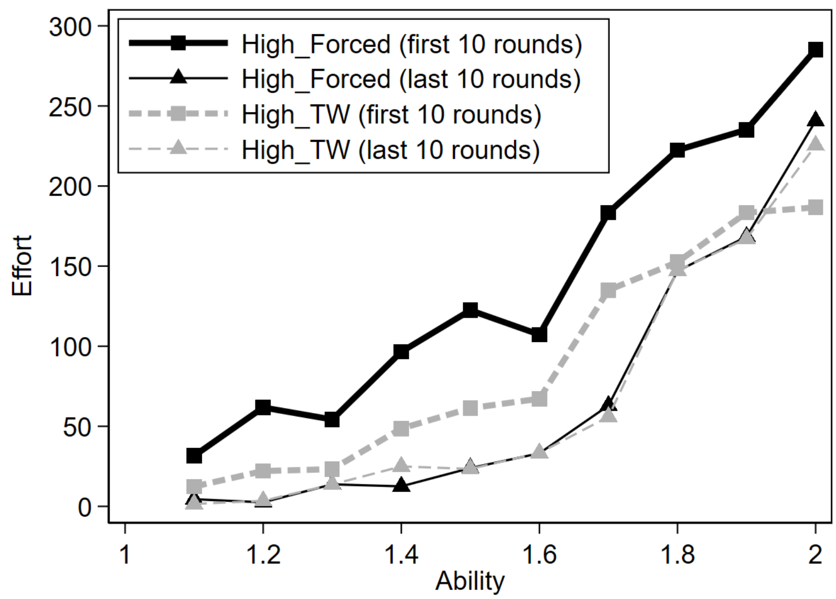
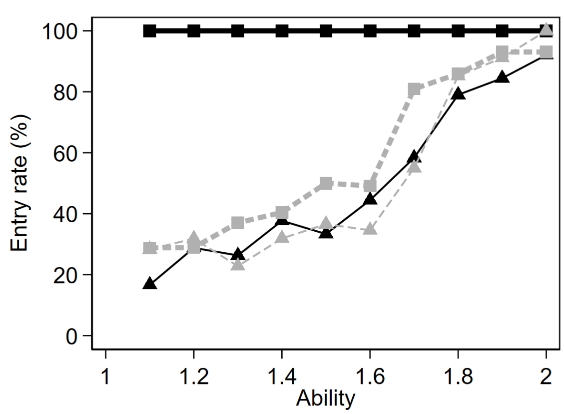


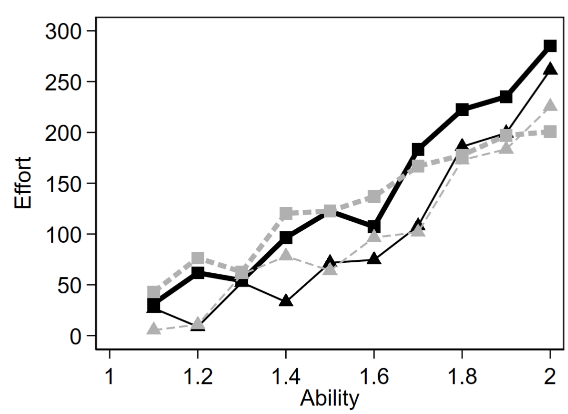
Figure B14: Average effort by ability in High_TW and High_Forced



(a) Average effort



(b) Entry rate



(c) Effort conditional on entry

Notes: The ability parameter is categorized into ten groups: [1, 1.1], (1.1, 1.2], . . . , (1.9, 2]. In the figure, we use the upper bound to indicate each group.

Table B1: Numerical calculations of percentage improvement of winner's effort and total effort

Panel A: Winner's effort improvement using the winner effort maximizing contest as opposed to the total effort maximizing contest

Weibull $F(t) = 1 - exp(-t^{\theta})$					Power $F(t) = (t-1)^{\theta}$				
	N=2	4	6	8		N=2	3	4	5
θ=1	1.42%	4.37%	4.75%	4.22%	θ=1	2.30%	1.46%	0.95%	0.67%
1.25	1.47%	3.94%	3.71%	3.01%	1.5	1.74%	1.13%	0.68%	0.44%
1.5	2.19%	3.83%	3.02%	2.23%	2	1.48%	0.88%	0.50%	0.31%
1.75	2.65%	3.49%	2.41%	1.70%	2.5	1.21%	0.70%	0.38%	0.23%
2	2.22%	2.86%	1.90%	1.33%	3	1.07%	0.58%	0.30%	0.18%
Quadratic $F(t) = \theta t^2 + (1-3\theta)t + (2\theta - 1)$					Exponential $F(t) = 1 - exp(-\theta t)$				
	N=2	3	4	5		N=2	5	8	11
θ=-0.4	1.42%	1.12%	0.84%	0.64%	θ=1	1.55%	4.87%	4.26%	3.32%
-0.2	1.84%	1.31%	0.92%	0.67%	3	1.48%	4.81%	4.24%	3.32%
0	2.30%	1.46%	0.95%	0.67%	5	1.55%	4.87%	4.25%	3.32%
0.2	2.34%	1.49%	0.93%	0.62%	7	1.33%	4.70%	4.21%	3.31%
0.4	2.09%	1.40%	0.84%	0.55%	9	1.71%	4.97%	4.29%	3.32%

Panel B: Total effort improvement using the total effort maximizing contest as opposed to the winner effort maximizing contest

Weibull $F(t) = 1 - exp(-t^{\theta})$					Power $F(t) = (t-1)^{\theta}$				
	N=2	4	6	8		N=2	3	4	5
θ=1	1.46%	4.90%	6.44%	7.97%	θ=1	3.70%	4.27%	4.40%	4.04%
1.25	1.62%	5.30%	6.35%	7.57%	1.5	2.78%	3.33%	3.46%	3.43%
1.5	1.59%	6.19%	6.03%	6.24%	2	2.60%	3.06%	3.05%	2.81%
1.75	1.58%	5.04%	7.14%	5.74%	2.5	2.27%	2.92%	2.68%	2.18%
2	2.48%	4.60%	4.93%	5.90%	3	2.09%	2.50%	2.41%	2.05%
Quadratic $F(t) = \theta t^2 + (1-3\theta)t + (2\theta - 1)$					Exponential $F(t) = 1 - exp(-\theta t)$				
	N=2	3	4	5		N=2	5	8	11
θ=-0.4	3.84%	4.36%	4.42%	4.41%	θ=1	1.45%	5.89%	7.51%	8.00%
-0.2	3.94%	4.36%	4.40%	4.38%	3	1.52%	5.79%	7.41%	8.10%
0	3.70%	4.27%	4.40%	4.04%	5	1.32%	5.89%	7.61%	8.10%
0.2	3.34%	3.86%	4.14%	3.90%	7	1.65%	5.60%	7.41%	8.09%
0.4	2.83%	3.63%	3.68%	3.56%	9	1.52%	5.79%	7.41%	**8.40%**

Notes: We examined four different one-parameter functional forms of the ability distribution and also varied the group size N. The percentage in each cell is the numerical calculation of the ratio improvement in terms of winner's effort (Panel A) and total effort (Panel B) when comparing the two optimal mechanisms, conditional on a specific ability distribution and group size. The liability K is always set to 0 which maximizes the ratio improvement for any given set of parameters. Since the optimal effort is linear in the prize budget V, the percentage improvement does not depend on the prize budget.

Table B2: Random effects regressions on the winner's effort and total effort

	Winner's effort		Total effort	
	(1) All rounds	(2) Last 10 rounds	(3) All rounds	(4) Last 10 rounds
High_TW	59.058***	49.008***	80.581***	59.946***
	(7.388)	(10.328)	(13.479)	(18.016)
Medium_TW	18.338*	10.638	25.685	15.404
	(10.832)	(10.166)	(19.137)	(15.379)
Low_W	9.465	1.988	13.604	9.146
	(8.046)	(8.464)	(14.409)	(13.001)
Low_T	11.475	-0.666	14.785	-1.492
	(8.719)	(9.827)	(15.216)	(14.320)
Zero_W	2.798	0.496	7.192	4.054
	(8.016)	(9.029)	(14.969)	(13.139)
Round	-1.518***	0.184	-2.726***	0.716
	(0.359)	(0.799)	(0.525)	(1.269)
Constant	135.796***	113.831***	194.924***	146.587***
	(6.495)	(14.123)	(12.894)	(22.270)
Clusters	36	36	36	36
N	2880	1440	2880	1440
H0: High_TW = Medium_TW	$p < 0.001$	$p < 0.001$	$p = 0.001$	$p = 0.014$
H0: High_TW = Low_W	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p = 0.002$
H0: High_TW = Low_T	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p = 0.001$
H0: High_TW = Zero_W	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p = 0.001$
H0: Medium_TW = Low_W	$p = 0.388$	$p = 0.270$	$p = 0.479$	$p = 0.637$
H0: Medium_TW = Low_T	$p = 0.526$	$p = 0.224$	$p = 0.540$	$p = 0.245$
H0: Medium_TW = Zero_W	$p = 0.130$	$p = 0.230$	$p = 0.292$	$p = 0.396$
H0: Low_W = Low_T	$p = 0.802$	$p = 0.720$	$p = 0.925$	$p = 0.375$
H0: Low_W = Zero_W	$p = 0.358$	$p = 0.813$	$p = 0.600$	$p = 0.630$

Notes: Standard errors clustered at the matching group level are in parentheses. Zero_T serves as the benchmark. *** $p < 0.01$.

Table B3: Summary statistics for entry and effort choices - last 10 rounds

	High_TW	Medium_TW	Low_W	Low_T	Zero_W	Zero_T
Entry rate						
All	53.1%	62.6%	73.2%	73.6%	66.3%	77.8%
High ability	91.2%	73.5%	83.3%	79.8%	79.0%	/
Low ability	35.4%	45.7%	57.4%	49.7%	46.5%	/
Above-cutoff rate if enter						
All	61.8%	67.0%	62.0%	80.2%	66.9%	100%
High ability	83.7%	78.6%	74.2%	83.2%	78.3%	/
Low ability	35.6%	38.0%	34.6%	61.6%	36.6%	/
Positive effort but below-cutoff rate if enter						
All	11.0%	10.0%	5.1%	3.6%	2.5%	0%
High ability	7.7%	7.8%	3.8%	2.8%	2.9%	/
Low ability	14.9%	15.5%	8.0%	8.2%	1.5%	/
Zero effort rate if enter						
All	27.2%	23.1%	32.8%	16.2%	30.6%	23.6%
High ability	8.7%	13.7%	21.9%	14.0%	18.8%	/
Low ability	49.4%	46.5%	57.4%	30.1%	61.8%	/
Average effort if enter						
All	136.7	92.1	76.0	70.7	81.4	67.6
High ability	192.3	117.7	99.2	79.2	102.2	/
Low ability	70.3	28.3	23.7	17.5	26.3	/

Notes: High (low) ability is determined by whether a contestant's ability parameter is above (below) the cutoff value in a round. This cutoff value is 1.218 in Low_T, 1.455 in Medium_TW, Low_W and Zero_W, and 1.707 in High_TW. "Above-cutoff rate if enter" refers to the frequency of contestants' efforts above the cutoff effort, which is 36.5 in Zero_W, 35.5 in Low_W, 4.5 in Low_T, 30.5 in Medium_TW and 136.5 in High_TW.

Table B4: Random effects regressions for entry and effort choices: Robustness check

	All rounds		Last 10 rounds	
	Pr(Entry)	Effort if enter	Pr(Entry)	Effort if enter
High_TW	-0.273***	65.871***	-0.392***	65.890***
	(0.035)	(7.909)	(0.042)	(10.190)
Medium_TW	-0.170***	25.199***	-0.225***	23.982***
	(0.039)	(8.337)	(0.042)	(8.900)
Low_W	-0.071	9.903	-0.081	9.283
	(0.071)	(6.748)	(0.074)	(8.093)
Low_T	-0.075*	9.852	-0.097*	2.323
	(0.042)	(6.557)	(0.050)	(8.966)
Zero_W	-0.173***	14.589*	-0.190***	12.921
	(0.041)	(8.195)	(0.057)	(9.612)
Ability	0.639***	160.097***	0.645***	160.033***
	(0.029)	(7.560)	(0.034)	(7.519)
Believe 1 enters	-0.090***	33.533***	-0.090***	31.461***
	(0.019)	(5.510)	(0.019)	(7.729)
Believe 2 enter	-0.334***	40.056***	-0.337***	41.021***
	(0.025)	(5.832)	(0.030)	(7.983)
Own entry	0.087***	-3.129	0.055***	-1.596
in previous round	(0.013)	(2.219)	(0.014)	(2.767)
No. of other entrants	0.013*	5.271***	-0.010	3.288
in previous round	(0.007)	(1.928)	(0.010)	(2.123)
Female	-0.013	6.990	-0.041	4.212
	(0.031)	(4.904)	(0.038)	(5.148)
Risk	0.028**	0.181	0.034***	0.551
	(0.011)	(2.461)	(0.013)	(2.732)
Competitive	0.018**	-0.568	0.021**	-0.704
	(0.009)	(2.107)	(0.010)	(2.099)
CRT	0.034***	-2.647	0.032***	-0.563
	(0.011)	(2.574)	(0.012)	(2.642)
Round	-0.001	-1.924***	0.000	-1.382***
	(0.002)	(0.246)	(0.002)	(0.468)
Clusters	24	36	36	36
N	8208	5506	4320	2927

Notes: Columns (1) and (3) report the average marginal effects from random effects probit regressions on the entry decision. Columns (2) and (4) report estimates from random effects linear regression on the effort choice for contestants who have entered the contest. Standard errors clustered at the matching group level are in parentheses. Zero_T serves as the benchmark. “Risk” is self-reported general attitudes toward risk-taking in daily life on the scale from 1 (not risk-taking at all) to 7 (extremely risk-taking). “Competitive” is self-reported general attitudes toward being competitive in daily life on the scale from 1 (not competitive at all) to 7 (extremely competitive). “CRT” refers to the Cognitive Reflection Test using the standard three questions developed by Frederick (2005) to assess cognitive ability. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Random effects regressions for entry and effort choices by treatment

	Pr(Entry)						Effort if enter					
	High_TW	Medium_TW	Low_W	Low_T	Zero_W	Zero_T	High_TW	Medium_TW	Low_W	Low_T	Zero_W	Zero_T
Ability	0.801***	0.661***	0.557***	0.572***	0.694***	0.391***	189.051***	169.782***	162.078***	155.148***	139.458***	137.820***
	(0.017)	(0.029)	(0.155)	(0.077)	(0.045)	(0.049)	(22.632)	(14.831)	(13.701)	(20.642)	(8.329)	(21.256)
Believe 1 enters	-0.171***	-0.162***	0.032	-0.001	-0.063**	0.048	55.382***	31.050***	24.235***	36.189***	24.360**	21.678**
	(0.035)	(0.036)	(0.115)	(0.073)	(0.031)	(0.067)	(16.386)	(2.446)	(5.396)	(5.294)	(9.708)	(10.001)
Believe 2 enter	-0.448***	-0.379***	-0.144	-0.243***	-0.325***	-0.116	77.727***	43.199***	28.809***	50.294***	22.470***	20.435*
	(0.031)	(0.061)	(0.158)	(0.069)	(0.047)	(0.080)	(17.010)	(4.086)	(8.098)	(3.087)	(6.503)	(11.881)
Female	0.016	-0.009	0.031	-0.016	-0.216	0.009	-3.806	16.788**	-7.141	11.766	25.484**	2.476
	(0.045)	(0.077)	(0.092)	(0.070)	(0.145)	(0.094)	(10.532)	(8.330)	(10.835)	(15.168)	(11.458)	(12.800)
Risk	0.052**	0.048***	0.071**	-0.007	0.001	0.042	-2.469	-4.138	-10.779	1.854	1.943	8.076**
	(0.020)	(0.013)	(0.033)	(0.028)	(0.040)	(0.041)	(10.631)	(2.967)	(8.710)	(4.072)	(6.532)	(3.815)
Competitive	0.029**	0.019	-0.021	0.018*	0.027	-0.009	-3.749	1.288	14.692	4.512	-1.533	-9.581**
	(0.014)	(0.015)	(0.051)	(0.011)	(0.027)	(0.029)	(4.212)	(7.419)	(9.264)	(4.194)	(4.000)	(3.763)
CRT	-0.009	0.028*	0.036	0.035	0.067***	0.061**	-5.455*	8.314**	-6.302	-2.132	-2.903	-4.583
	(0.017)	(0.017)	(0.027)	(0.046)	(0.024)	(0.025)	(3.094)	(4.236)	(6.717)	(7.906)	(9.114)	(3.393)
Round	-0.017***	-0.006***	0.003	-0.001	0.006	0.008***	-0.750	-1.365*	-1.811***	-1.729***	-1.609***	-1.614***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.742)	(0.730)	(0.558)	(0.460)	(0.411)	(0.303)
Clusters	6	6	6	6	6	6	6	6	6	6	6	6
N	1440	1440	1440	1440	1440	1440	814	918	1030	1045	920	1083

Notes: Columns (1) to (6) report the average marginal effects from random effects probit regressions on the entry decision. Columns (7) to (12) report estimates from random effects linear regression on the effort choice for contestants who have entered the contest. Standard errors clustered at the matching group level are in parentheses. "Risk" is self-reported general attitudes toward risk-taking in daily life on the scale from 1 (not risk-taking at all) to 7 (extremely risk-taking). "Competitive" is self-reported general attitudes toward being competitive in daily life on the scale from 1 (not competitive at all) to 7 (extremely competitive). 'CRT" refers to the Cognitive Reflection Test using the standard three questions developed by Frederick (2005) to assess cognitive ability. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: Random effects regressions for entry and effort choices of high-ability individuals by treatment

	Pr(Entry)					Effort if enter				
	High_TW	Medium_TW	Low_W	Low_T	Zero_W	High_TW	Medium_TW	Low_W	Low_T	Zero_W
Ability	0.146	0.885***	0.350	0.530***	0.804***	132.036***	211.246***	255.485***	184.806***	186.976***
	(0.127)	(0.111)	(0.260)	(0.073)	(0.132)	(17.384)	(23.121)	(4.119)	(19.570)	(13.250)
Believe 1 enters	-0.002	-0.095***	0.076	0.010	-0.021	81.827***	55.065***	32.565***	43.751***	35.481***
	(0.040)	(0.033)	(0.140)	(0.057)	(0.017)	(21.378)	(9.631)	(7.617)	(2.893)	(11.492)
Believe 2 enter	-0.066	-0.232***	0.014	-0.179***	-0.214***	98.992***	70.194***	38.594***	57.694***	34.604***
	(0.051)	(0.057)	(0.140)	(0.065)	(0.071)	(18.547)	(10.345)	(10.614)	(3.586)	(9.320)
Female	0.002	0.020	0.000	0.015	-0.056	-14.536	11.531	-13.016	12.988	21.414
	(0.009)	(0.059)	(0.057)	(0.064)	(0.119)	(10.011)	(11.287)	(15.527)	(14.477)	(16.921)
Risk	0.001	0.038**	0.020	-0.002	0.014	-3.990	-4.101	2.889	-9.635	1.622
	(0.013)	(0.019)	(0.024)	(0.032)	(0.033)	(12.255)	(3.705)	(6.020)	(10.309)	(4.444)
Competitive	0.010	0.018	0.014	0.019	0.040	0.398	3.432	-0.261	12.316	5.066
	(0.010)	(0.024)	(0.037)	(0.013)	(0.031)	(5.274)	(8.619)	(4.972)	(10.333)	(4.628)
CRT	-0.005	0.018	0.010	0.032	0.072*	0.122	8.730*	-1.371	-3.240	0.855
	(0.008)	(0.012)	(0.026)	(0.046)	(0.041)	(2.697)	(5.183)	(10.753)	(8.658)	(9.116)
Round	-0.002	-0.003*	0.001	0.000	0.008***	0.128	-1.060	-1.535***	-1.372***	-1.966***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.537)	(0.845)	(0.500)	(0.468)	(0.490)
Clusters	6	6	6	6	6	6	6	6	6	6
N	444	828	828	1173	828	404	632	688	914	640

Notes: Columns (1) to (5) report the average marginal effects from random effects probit regressions on the entry decision. Columns (6) to (10) report estimates from random effects linear regression on the effort choice for contestants who have entered the contest. Standard errors clustered at the matching group level are in parentheses. "Risk" is self-reported general attitudes toward risk-taking in daily life on the scale from 1 (not risk-taking at all) to 7 (extremely risk-taking). "Competitive" is self-reported general attitudes toward being competitive in daily life on the scale from 1 (not competitive at all) to 7 (extremely competitive). 'CRT" refers to the Cognitive Reflection Test using the standard three questions developed by Frederick (2005) to assess cognitive ability. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B7: Random effects regressions for entry and effort choices of low-ability individuals by treatment

	Pr(Entry)					Effort if enter				
	High_TW	Medium_TW	Low_W	Low_T	Zero_W	High_TW	Medium_TW	Low_W	Low_T	Zero_W
Ability	0.660***	0.366**	0.578***	1.352**	0.653***	164.406***	69.020***	6.324	-75.265**	40.747***
	(0.069)	(0.157)	(0.169)	(0.558)	(0.158)	(26.758)	(23.406)	(25.503)	(33.898)	(10.063)
Believe 1 enters	-0.258***	-0.200***	-0.034	0.036	-0.174**	47.611***	8.955	9.199	27.920*	3.224
	(0.045)	(0.040)	(0.097)	(0.134)	(0.078)	(17.057)	(6.324)	(6.203)	(14.852)	(9.944)
Believe 2 enter	-0.574***	-0.579***	-0.349*	-0.417**	-0.483***	68.614***	2.772	6.485	45.851***	2.014
	(0.040)	(0.082)	(0.193)	(0.184)	(0.093)	(22.644)	(8.010)	(7.548)	(16.955)	(9.122)
Female	0.010	-0.044	0.089	-0.103	-0.369*	2.433	21.861**	1.566	14.581	41.892***
	(0.057)	(0.133)	(0.155)	(0.089)	(0.191)	(15.617)	(10.216)	(11.827)	(13.716)	(4.974)
Risk	0.067***	0.073***	0.174***	-0.010	0.015	-2.646	-2.913	-16.275**	3.340	2.863
	(0.021)	(0.013)	(0.047)	(0.044)	(0.046)	(9.112)	(2.626)	(6.565)	(2.985)	(9.818)
Competitive	0.031	-0.003	-0.084	0.019	0.001	-6.008	-1.038	20.941***	1.200	-4.214
	(0.020)	(0.014)	(0.070)	(0.037)	(0.030)	(5.106)	(5.877)	(7.092)	(3.001)	(3.799)
CRT	-0.013	0.036	0.106***	0.053	0.053**	-9.956*	8.229**	-18.970***	-15.414	-2.531
	(0.021)	(0.032)	(0.030)	(0.086)	(0.020)	(5.558)	(3.411)	(3.874)	(11.068)	(7.531)
Round	-0.022***	-0.009*	0.006	-0.002	0.006	-1.676	-2.122**	-1.950***	-0.569	-1.464**
	(0.003)	(0.005)	(0.005)	(0.002)	(0.005)	(1.113)	(0.934)	(0.704)	(0.639)	(0.566)
Clusters	6	6	6	6	6	6	6	6	6	6
N	996	612	612	267	612	410	286	342	131	280

Notes: Columns (1) to (5) report the average marginal effects from random effects probit regressions on the entry decision. Columns (6) to (10) report estimates from random effects linear regression on the effort choice for contestants who have entered the contest. Standard errors clustered at the matching group level are in parentheses. "Risk" is self-reported general attitudes toward risk-taking in daily life on the scale from 1 (not risk-taking at all) to 7 (extremely risk-taking). "Competitive" is self-reported general attitudes toward being competitive in daily life on the scale from 1 (not competitive at all) to 7 (extremely competitive). 'CRT" refers to the Cognitive Reflection Test using the standard three questions developed by Frederick (2005) to assess cognitive ability. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B8: Random effects regressions on the winner's effort and total effort in High_TW and High_Forced

	Winner's effort		Total effort	
	First 10 rounds	Last 10 rounds	First 10 rounds	Last 10 rounds
High_Forced	88.996***	4.100	153.958***	4.100
	(10.129)	(8.849)	(16.310)	(8.849)
Round	5.512**	-4.141**	2.444	-4.141**
	(2.233)	(2.111)	(3.515)	(2.111)
Constant	161.831***	229.884***	262.685***	229.884***
	(14.618)	(30.388)	(26.556)	(30.388)
Clusters	12	12	12	12
N	480	480	480	480

Notes: Standard errors clustered at the matching group level are in parentheses. High_TW serves as the benchmark. *** $p < 0.01$.

Table B9: Random effects regressions for effort conditional on entry in High_TW and High_Forced during the first 10 rounds

	Effort if enter
High_Forced	3.312
	(15.746)
Ability	246.109***
	(17.331)
Believe 1 enters	59.273***
	(20.660)
Believe 2 enter	77.299***
	(25.578)
Female	-16.105
	(10.297)
Risk	11.770*
	(6.219)
Competitive	2.436
	(5.043)
CRT	-4.710
	(4.110)
Round	2.036*
	(1.061)
Constant	-359.528***
	(54.180)
Clusters	12
N	1152

Notes: "Believe 2 enter" is always coded as 1 for the first 10 rounds in High_Forced since this is always true by design. The table reports estimates from random effects linear regression on the effort choice for contestants who have entered the contest. Standard errors clustered at the matching group level are in parentheses. High_TW serves as the benchmark. "Risk" is self-reported general attitudes toward risk-taking in daily life on the scale from 1 (not risk-taking at all) to 7 (extremely risk-taking). "Competitive" is self-reported general attitudes toward being competitive in daily life on the scale from 1 (not competitive at all) to 7 (extremely competitive). "CRT" refers to the Cognitive Reflection Test using the standard three questions developed by Frederick (2005) to assess cognitive ability. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Experimental Instructions

C.1 Instructions for Medium_TW

[The instructions for High_TW, Low_T and Low_W are omitted here since they only differ in terms of the entry fee and minimum amount of investment.]

You are about to participate in an experiment. The instructions are the same for all participants. Please read them carefully. No communication is allowed during the experiment. If you have any question, please raise your hand and an experimenter will come to help you.

You have received 15 Yuan for showing up on time. You may earn more money by making decisions in the experiment. The points you may earn depends on your decision and on other participants' decisions. At the end of the experiment, all points you earn will be converted to RMB at the rate of 25 points for 1 RMB. Both your identity and your decisions are strictly anonymous throughout the experiment.

Overview

This experiment consists of 20 periods. At the beginning of each period, you will be randomly matched into a group of 3 participants. Thus, you will be in a different group every period.

In each round, you must first decide whether to enter into a contest to compete against other group members to win a prize. The value of the total prize depends on the number of group members who choose to enter:

- If you choose **not to enter into the contest**, then you have no further decision to make in this round.
- If you choose **to enter into the contest**, then you must pay an entry fee worth 10.5 points and also decide how much resource to invest in the contest.

At the beginning of each round, each participant will receive an endowment of 300 points to cover the entry fee and investment cost in the contest.

In the following, we will explain in detail the determination of the total prize and the contest rule.

Total prize

The total prize will consist of two components:

1. The base prize: 120 points.
2. The total amount of entry fees collected from all contestants

Therefore, **the total prize in each round = 120 + n*entry fee**, where n is the number of contestants in your group. For example, if two group members choose to enter in a round, the total prize in that round is equal to 120 + 2*entry fee.

Note: you will not be informed about how many group members choose to enter or about the exact value of the total prize until the end of each round.

Prediction of the number of contestants

Whether or not you choose to enter in a round, you will be asked to predict the number of contestants in your group (including yourself). If your prediction is correct, you will earn additional 10 points.

Investment cost

If you choose to enter, then you also need to decide how much resource to invest in the contest. Your investment cost is equal to:

Investment cost = invested resource / productivity

where **productivity** can take any value from **1.00 to 2.00 (up to 2 decimal points)**. That is, the higher your productivity, the lower your investment cost for a given amount of invested resource. The computer will randomly and independently draw the productivity value for everyone in your group. In every period everyone will have new draws.

Note: at the beginning of each period ,you will be informed of your productivity value. But you will not know other group members' productivity values.

Contest rule

If you choose to enter, your earnings from the contest are determined by the following conditions:

- Condition 1: whether any other group members choose to enter.
  - Case 1: if no other group member chooses to enter, then no matter how much resource you invest, you will automatically win the total prize, i.e., **the base prize of 120 points plus your returned entry fee**. Your earnings in this round is: 300 - investment cost + 120.
  - If at least one other group member chooses to enter, then we consider Condition 2.
- Condition 2: whether at least one contestant's invested resource is greater than 30.5, i.e., the minimum amount of investment.
  - Case 2: if no contestant's invested resource is greater than 30.5, then all contestants (those who enter) **share the total prize, i.e., sharing the base prize of 120 points plus your returned entry fee**. Your earnings in this round is: 300 - investment cost + 120/n, where n is the number of contestants (including yourself).
  - If at least one contestant's invested resource is greater than 30.5, then we consider Condition 3.
- Condition 3: whether you invest the highest amount of resource.

– Case 3: if you invest the highest amount of resource, then you will win the total prize all by yourself, i.e., **the base prize of 120 points plus all contestants' entry fees (including yours)**. Your earnings in this round is: 300 - investment cost + 120 + n*entry fee - entry fee = 300 - investment cost + 120 + (n - 1)*entry fee, where n is the number of contestants (including yourself).

– Case 4: if you invest the highest amount of resource but there are also other group members investing the same amount, then all winners share the total prize, i.e., **the base prize of 120 points plus all contestants' entry fees (including yours)**. Your earnings in this round is: 300 - investment cost + (120 + n*entry fee)/m - entry fee, where m is the number of contestants who invest the highest amount of resource (including yourself), n $\geq$ m.

– Case 5: if your invested resource is not the highest, then you do not win the prize. Your earnings in this round is: 300 - investment cost - entry fee.

Note: the situations where your entry fee will be returned include 1) only you enter into the contest; 2) no contestant's invested resource is greater than 30.5; 3) your invested resource is the highest. In other words, only when someone else but not you invests the highest amount of resource exceeding 30.5 will your entry fee not be returned.

If you decide not to enter into in the contest, your earnings are equal to your endowment of 300 points.

Below we will demonstrate the payoff calculation through two examples.

Example 1

ID	Productivity	Enter	Resource	Investment Cost	Win?	Entry fee returned?	Payoff calculation
1	1.50	No	0	0	Yes	Yes	300-0+120/2=360
2	2.00	Yes	30	15	Yes	Yes	300-15+120/2=345
3	1.00	No	/	/	No	/	300

Example 2

ID	Productivity	Enter	Resource	Investment Cost	Win?	Entry fee returned?	Payoff calculation
1	1.50	Yes	150	100	No	No	300-100-10.5=189.5
2	2.00	Yes	200	100	Yes	Yes	300-100+120+(3-1)*10.5=341
3	1.00	Yes	20	20	No	No	300-20-10.5=269.5

Feedback and final payoff

At the end of each period, you will be informed about the number of contestants, the highest invested resource, and your period earnings. At the end of the experiment, **five out of 20 periods** will be drawn randomly to determine your earnings. The earnings you receive in these five periods will be summed and converted into RMB.

Some common questions: What if my earnings are negative? They will be compensated with your other gains. If at the end of the session your earnings are negative, you will receive 15 Yuan, the participation payment. Are there any questions?

C.2 Instructions for Zero_W

You are about to participate in an experiment. The instructions are the same for all participants. Please read them carefully. No communication is allowed during the experiment. If you have any question, please raise your hand and an experimenter will come to help you.

You have received 15 Yuan for showing up on time. You may earn more money by making decisions in the experiment. The points you may earn depends on your decision and on other participants' decisions. At the end of the experiment, all points you earn will be converted to RMB at the rate of 25 points for 1 RMB. Both your identity and your decisions are strictly anonymous throughout the experiment.

Overview

This experiment consists of 20 periods. At the beginning of each period, you will be randomly matched into a group of 3 participants. Thus, you will be in a different group every period.

In each round, you must first decide whether to enter into a contest to compete against other group members to win a prize.

- If you choose **not to enter into the contest**, then you have no further decision to make in this round.
- If you choose **to enter into the contest**, then you must also decide how much resource to invest in the contest.

At the beginning of each round, each participant will receive an endowment of 300 points to cover the investment cost in the contest.

In the following, we will explain in detail the determination of the total prize and the contest rule.

Total prize

The total prize will be 120 points.

Note: you will not be informed about how many group members choose to enter until the end of each round.

Prediction of the number of contestants

Whether or not you choose to enter in a round, you will be asked to predict the number of contestants in your group (including yourself). If your prediction is correct, you will earn additional 10 points.

Investment cost

If you choose to enter, then you also need to decide how much resource to invest in the contest. Your investment cost is equal to:

Investment cost = invested resource / productivity

where **productivity** can take any value from **1.00 to 2.00 (up to 2 decimal points)**. That is, the higher your productivity, the lower your investment cost for a given amount of invested resource. The computer will randomly and independently draw the productivity value for everyone in your group. In every period everyone will have new draws.

Note: at the beginning of each period, you will be informed of your productivity value. But you will not know other group members' productivity values.

Contest rule

If you choose to enter, your earnings from the contest are determined by the following conditions:

- Condition 1: whether at least one contestant's invested resource is greater than 36.5, i.e., the minimum amount of investment.
  - Case 1: if no contestant's invested resource is greater than 36.5, then no one will obtain any prize. Your earnings in this round is: 300 - investment cost.
  - If at least one contestant's invested resource is greater than 36.5, then we consider Condition 2.
- Condition 2: whether you invest the highest amount of resource.
  - Case 2: if you invest the highest amount of resource, then you will win the total prize all by yourself. Your earnings in this round is: 300 - investment cost + 120.
  - Case 3: if you invest the highest amount of resource but there are also other group members investing the same amount, then all winners share the total prize. Your earnings in this round is: 300 - investment cost + 120/m, where m is the number of contestants who invest the highest amount of resource (including yourself).
  - Case 4: if your invested resource is not the highest, then you do not win the prize. Your earnings in this round is: 300 - investment cost.

If you decide not to enter into in the contest, your earnings are equal to your endowment of 300 points.

Below we will demonstrate the payoff calculation through two examples.

Example 1

ID	Productivity	Enter	Resource	Investment Cost	Win?	Payoff calculation
1	1.50	No	0	0	No	300-0=300
2	2.00	Yes	30	15	No	300-15=285
3	1.00	No	/	/	No	300

Example 2

ID	Productivity	Enter	Resource	Investment Cost	Win?	Payoff calculation
1	1.50	Yes	150	100	No	300-100=200
2	2.00	Yes	200	100	Yes	300-100+120=320
3	1.00	Yes	20	20	No	300-20=280

Feedback and final payoff

At the end of each period, you will be informed about the number of contestants, the highest invested resource, and your period earnings. At the end of the experiment, **five out of 20 periods** will be drawn randomly to determine your earnings. The earnings you receive in these five periods will be summed and converted into RMB.

Some common questions: What if my earnings are negative? They will be compensated with your other gains. If at the end of the session your earnings are negative, you will receive 15 Yuan, the participation payment. Are there any questions?

C.3 Instructions for Zero_T

You are about to participate in an experiment. The instructions are the same for all participants. Please read them carefully. No communication is allowed during the experiment. If you have any question, please raise your hand and an experimenter will come to help you.

You have received 15 Yuan for showing up on time. You may earn more money by making decisions in the experiment. The points you may earn depends on your decision and on other participants' decisions. At the end of the experiment, all points you earn will be converted to RMB at the rate of 25 points for 1 RMB. Both your identity and your decisions are strictly anonymous throughout the experiment.

Overview

This experiment consists of 20 periods. At the beginning of each period, you will be randomly matched into a group of 3 participants. Thus, you will be in a different group every period.

In each round, you must first decide whether to enter into a contest to compete against other group members to win a prize.

- If you choose **not to enter into the contest**, then you have no further decision to make in this round.

- If you choose **to enter into the contest**, then you must also decide how much resource to invest in the contest.

At the beginning of each round, each participant will receive an endowment of 300 points to cover the investment cost in the contest.

In the following, we will explain in detail the determination of the total prize and the contest rule.

Total prize

The total prize will be 120 points.

<u>Note: you will not be informed about how many group members choose to enter until the end of each round.</u>

Prediction of the number of contestants

Whether or not you choose to enter in a round, you will be asked to predict the number of contestants in your group (including yourself). If your prediction is correct, you will earn additional 10 points.

Investment cost

If you choose to enter, then you also need to decide how much resource to invest in the contest. Your investment cost is equal to:

Investment cost = invested resource / productivity

where **productivity** can take any value from **1.00 to 2.00 (up to 2 decimal points)**. That is, the higher your productivity, the lower your investment cost for a given amount of invested resource. The computer will randomly and independently draw the productivity value for everyone in your group. In every period everyone will have new draws.

<u>Note: at the beginning of each period, you will be informed of your productivity value. But you will not know other group members' productivity values.</u>

Contest rule

If you choose to enter, your earnings from the contest are determined by the following conditions:

- Condition 1: whether any other group members choose to enter.
  - Case 1: if no other group member chooses to enter, then no matter how much resource you invest, you will automatically win the total prize. Your earnings in this round is: 300 - investment cost + 120.
  - If at least one other group member chooses to enter, then we consider Condition 2.
- Condition 2: whether you invest the highest amount of resource.

- Case 2: if you invest the highest amount of resource, then you will win the total prize all by yourself. Your earnings in this round is: 300 - investment cost + 120.
- Case 3: if you invest the highest amount of resource but there are also other group members investing the same amount, then all winners share the total prize. Your earnings in this round is: 300 - investment cost + 120/m, where m is the number of contestants who invest the highest amount of resource (including yourself).
- Case 4: if your invested resource is not the highest, then you do not win the prize. Your earnings in this round is: 300 - investment cost.

If you decide not to enter into in the contest, your earnings are equal to your endowment of 300 points.

Below we will demonstrate the payoff calculation through two examples.

Example 1

ID	Productivity	Enter	Resource	Investment Cost	Win?	Payoff calculation
1	1.50	No	0	0	No	300-0=300
2	2.00	Yes	30	15	Yes	300-15+120=405
3	1.00	No	/	/	No	300

Example 2

ID	Productivity	Enter	Resource	Investment Cost	Win?	Payoff calculation
1	1.50	Yes	150	100	No	300-100=200
2	2.00	Yes	200	100	Yes	300-100+120=320
3	1.00	Yes	20	20	No	300-20=280

Feedback and final payoff

At the end of each period, you will be informed about the number of contestants, the highest invested resource, and your period earnings. At the end of the experiment, **five out of 20 periods** will be drawn randomly to determine your earnings. The earnings you receive in these five periods will be summed and converted into RMB.

Some common questions: What if my earnings are negative? They will be compensated with your other gains. If at the end of the session your earnings are negative, you will receive 15 Yuan, the participation payment. Are there any questions?