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When to disclose the number of contestants: Theory and experimental evidence[☆]

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This paper investigates whether it is optimal for a contest organizer to disclose the actual number of contestants for total effort optimization when entry in a contest is costly and endogenous. Our model suggests that in a Tullock (1980) contest, the answer depends on the convexity of the cost of effort function. Even though the equilibrium entry rate and rent dissipation are invariant to the disclosure policy, disclosing (concealing) the actual number of entrants can lead to a higher total effort when the cost function is concave (convex). To test these theoretical predictions, we design a 2×3 between-subjects laboratory experiment using lottery contests. We vary the disclosure policy (fully disclosed vs. fully concealed) in one dimension and the curvature of the cost of effort function (concave, linear, or convex) in the other dimension. Our results are largely consistent with the theoretical predictions regarding the optimal disclosure policy, despite the presence of moderate over-entry and over-exertion behavior that is commonly observed in experimental studies of contests.

1. Introduction

Contests, in which a number of players exert costly and irreversible effort to compete for a limited number of prizes are ubiquitous. Most of the existing literature on contest theory and experiments assume that the number of contestants is fixed and common knowledge.[1] However, in real-life examples, decisions to enter a contest often involve explicit up-front participation cost or opportunity cost (of the time, effort and resources spent in the decision-making process), or both. Consequently, the number of actual participants in a contest is usually determined endogenously. For example, R&D firms must collect project-related background information, set up proper equipment and facilities, and select which innovation to undertake from a variety of potential projects; Academics aiming to compete for a research grant are often required to

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[1] See Konrad (2009) and Fu and Wu (2019) for reviews on contest theories and Dechenaux et al. (2015) for a survey of contest experiments.

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conduct preliminary research before writing a formal application; Employees who are not content with their current job should decide whether it is worth the effort and time updating their resumes and looking for a new job. Similar arguments can be applied to sports, lobbying or rent-seeking, and crowd-sourcing contests.

While there is *ex-ante* population uncertainty for both the contest organizer and potential contestants, the organizer usually observes the actual number of contestants after entry decisions have been made. Therefore, there is *ex-post* information asymmetry between the organizer and the contestants if the organizer does not reveal this information. In sports contests, athletes are often aware of the number of competitors they are facing, whereas firms (in R&D races), job seekers, lobbyists and participants in crowd-sourcing contests may not know this information. Disclosing or concealing the actual number of contestants prior to its realization could affect the potential participants' entry decisions and effort choices. Sometimes organizers have the freedom and authority to stipulate specific disclosure policies (e.g., in crowd-sourcing or labor-market contests), while other times they are bound by law or the nature of the contests (e.g., in lobbying or sports contests). This information asymmetry naturally raises the question of whether it is optimal for a contest organizer (who has commitment power) to commit to a disclosure policy before observing the actual number of contestants.

In this paper, we aim to address this question both theoretically and empirically using a laboratory experiment. In particular, we focus on the relationship between the optimal disclosure policy and the curvature of the cost-of-effort function. The existing literature on optimal disclosure policy (Lim and Matros, 2009; Fu et al., 2016; Feng and Lu, 2016; Boosey et al., 2017) has focused on contests with exogenous stochastic entry and linear cost of effort. Both Lim and Matros (2009) and Aycinena and Rentschler (2019) show that, when the cost of effort is linear, the total effort elicited from all contestants is invariant to disclosure policy. Lim and Matros (2009) further suggest that, even if the strategic organizer could choose a disclosure policy that is contingent on the number of contestants, to maximize total effort, she would always prefer to reveal the number of contestants after observing this information. Focusing on how the curvature of the cost-of-effort function affects optimal disclosure policy, our paper sheds new light on this problem: Depending on whether the contest organizer's objective is to maximize or minimize the total effort expended by all contestants, the optimal disclosure policy should vary accordingly if the cost-of-effort function is non-linear.[2]

We model the contest as a two-stage game in which the potential participants first decide whether to incur a fixed cost to enter the contest in Stage 1, and then make their effort choices to compete for a prize in Stage 2. In addition, we add a preliminary stage (Stage 0), during which the contest organizer must pre-commit to either fully disclosing or fully concealing the actual number of contestants after entry decisions have been made in Stage 1. Adopting the well-studied Tullock (1980) contest, we predict that even though the equilibrium entry probabilities and rent-dissipation rates are invariant to the disclosure policy in all cost structures, fully disclosing (concealing) the number of entrants will lead to a higher expected total effort when the cost of effort function is concave (convex). Similar to Lim and Matros (2009), disclosure policy is irrelevant for eliciting total effort when the cost of effort is linear even if entry is endogenously determined.

Fully disclosing or concealing the actual number of entrants in contests (i.e., a *Disclosure* policy or a *Concealment* policy) involves different equilibrium concepts from the perspective of game theory. However, regardless of the disclosure policy, the *ex-ante* expected payoff from entering the contest should offset the cost of entry in equilibrium. Therefore, the equilibrium entry rate and the (expected) total cost of effort and rent dissipation rate should be the same under different disclosure policies. Given the same equilibrium entry rate, the disclosure policy only affects the expected total effort through individuals' effort choices. When the actual number of entrants is disclosed, individual's equilibrium effort decreases with the actual number of entrants. Moreover, when the cost function is concave, a contestant with a decreasing marginal cost of effort is motivated to put even more effort in contests with less entrants. Hence, a more favorable contest (with a small number of entrants) *motivates* contestants more than a less favorable contest (with a large number of entrants) *demotivates* them. This leads contestants to behave as if they were risk-loving when supplying effort. In contrast, the equilibrium effort of their counterparts under a *Concealment* policy is uniform. As a result, the expected total effort is higher when the actual number of entrants is disclosed than when it is concealed. Conversely, when the cost function is convex, the contestants behave as if they were risk-averse (as a contest with a small number of contestants motivates contestants less than a contest with a large number of contestants demotivates them), hence the expected total effort is higher when the actual number of entrants is concealed.

To test these theoretical predictions, we conducted a 2×3 between-subjects experiment at Wuhan University (China) at the end of 2017. We manipulate the disclosure policy (fully disclosed or fully concealed) or the curvature of the cost function (concave, linear, or convex), one at a time. Our experimental results provide reasonably good support for our model predictions. First, given a certain cost structure the participants enter the contests with similar probabilities, irrespective of whether the actual number of entrants is disclosed. Second, in line with theory, the total cost of effort (and rent dissipation) is not significantly different across disclosure policies for a given cost structure, especially when the data from the second half of the experimental sessions are considered. Third, as predicted, the average total effort is insensitive to the disclosure policy when the cost function is linear, whereas it is significantly higher in the disclosed treatment when the cost function is concave. The only deviation from our theoretical predictions is when the cost function is convex: in this scenario, although

[2] In contest literature, "effort" is broadly used to represent time, money, physical or mental endeavor, or other resources invested in the competition. Fully identifying the curvature of the cost-of-effort function is not straightforward in real-world contests since they often involve different types of "effort" across different stages. Nonetheless, it is reasonable to argue that when "effort" mostly involves scarce resources like time or money, the "effort" cost function is likely to be convex, whereas when "effort" exertion involves repetition and learning, the "effort" cost function is likely to be concave.

the average total effort is higher in the concealed treatment (following the direction of the prediction), the difference is not statistically significant. Finally, the data at the individual level show moderate levels of over-entry (particularly when the cost function is concave) and over-exertion (particularly when the cost function is convex), which are commonly observed in previous contest experiments.

Our paper is broadly related to the theoretical and experimental literature on contests with *ex ante* population uncertainty. In the growing theoretical literature, population uncertainty is either modeled as exogenous stochastic entry, in which potential contestants enter with a given probability (Higgins et al., 1985; Myerson and Wärneryd, 2006; Münster, 2006; Lim and Matros, 2009; Fu et al., 2011; Kahana and Klunover, 2015; 2016; Ryvkin and Drugov, 2020), or driven by endogenous entry decisions made before a contest (Higgins et al., 1985; Fu and Lu, 2010; Kaplan and Sela, 2010; Fu et al., 2015). While Higgins et al. (1985), Münster (2006), and Myerson and Wärneryd (2006) pioneered the theoretical models of contests under stochastic entry, Lim and Matros (2009) and Fu et al. (2011) are the first papers to examine whether contest organizers should reveal the actual number of entrants. Extending on Lim and Matros (2009) which finds that the expected total effort does not depend on the disclosure policy when the cost of effort is linear, Fu et al. (2011) adopt a more general ratio-form contest success function, with the standard Tullock contest as a special case.[3] Similarly, they find that the optimal disclosure policy depends on the property of the characteristic function: fully disclosing (concealing) the actual number of entrants generates a higher expected total effort when the characteristic function is strictly concave (convex).[4] Our paper consider an endogenous-entry model that is similar to Fu et al. (2015) and provide experimental tests for our theoretical predictions.[5]

Compared with the theoretical literature on contests with *ex ante* population uncertainty, the experimental literature is sparse. Only a handful of studies examine contests with endogenous entry. Anderson and Stafford (2003) investigate how entry in rent-seeking contests and contest expenditure are affected by the available number of participants, cost heterogeneity, and the entry fee. Cason et al. (2010) compare entry in winner-take-all and proportional-prize contests. Morgan et al. (2012) and Morgan et al. (2016) allow participants to choose to enter sequentially in continuous time, and the number of entrants at each time-point is observable to all participants. Hammond et al. (2019) study all-pay contests in which bidders have private valuations to explore how to set a prize-augmenting entry fee to elicit more effort, when bids must be made without knowing the number of entrants. Liu et al. (2014) use field experimental data collected from the online crowd-sourcing platform Taskcn to study how contest participation and submission quality depend on the size of the reward and the presence of a soft reserve or early high-quality submission. Adamson and Kimbrough (2021) examine both theoretically and experimentally how variation in different costs affects contests, with an very interesting focus on the spacial element of conflicts, i.e, the size and the shape of the territory. None of the aforementioned studies investigate the optimal disclosure policy and the actual number of entrants is either fully disclosed or fully concealed throughout the contests.[6]

The experimental studies closest to ours are Aycinena and Rentschler (2019) and Boosey et al. (2017, 2020). While Aycinena and Rentschler (2019) studies (both theoretically and experimentally) endogenous entry decisions and disclosure policy in all-pay contests with private values and linear effort cost, Boosey et al. (2017) test the theoretical predictions of Lim and Matros (2009) in lottery contests with stochastic entry and linear cost of effort. Boosey et al. (2020) further study the optimal disclosure policy in lottery contests under endogenous entry. Our paper shares one dimension of the experimental variation with Boosey et al. (2020), namely whether the actual number of entrants is fully disclosed or concealed. Regarding the other dimension, while Boosey et al. (2020) vary the outside option (low or high) so that the endogenous entry probability is high or low, we change the curvature of the cost function (keeping the entry cost constant across all treatments). The two treatments of our experiment with a linear cost (under the *Disclosure* or *Concealment* policy) are similar to the two treatments with the low outside option in Boosey et al. (2020). It is reassuring to note that all four treatments confirm that the expected total effort is independent of the prevailing disclosure policy when the cost of effort is linear.

Our paper is the first to provide insights to contest organizers on the optimal disclosure policy, when the cost of effort is considered to be non-linear. The optimal disclosure policy varies depending on whether the organizer's objective is to maximize or minimize the total effort. For example, in labor markets, an employer who aims to maximize the total effort from job applicants, should disclose the number of applicants if the cost of applying is perceived to be concave. Interestingly, Gee (2019) conducted a large-scale field study about online job applications via LinkedIn, and found that candidates were more likely to complete their applications when they can observe the number of applicants for a given job opening, which

[3] Feng and Lu (2016) study a wider range of disclosure policies that allow for partial disclosure (concealment) using a Bayesian persuasion approach and find that partial disclosure is always sub-optimal, drawing similar conclusions to Fu et al. (2011). Ryvkin and Drugov (2020) further generalize the results of Fu et al. (2011) to arbitrary tournaments and arbitrary distributions of the number of players. They also show that the optimal disclosure policy depends on the shape of players' cost function in winner-take-all rank-order tournaments.

[4] The ratio-form contest success function is $p_i = f(x_i)/\sum_{j=1}^{N} f(x_j)$ and $H(\cdot) = f(\cdot)/f'(\cdot)$ is defined as the characteristic function.

[5] While Fu et al. (2015) establish a symmetric entry-bidding equilibrium under a wide class of contest technologies, and investigate how bidding efficiency and optimal design are affected by relevant institutional elements (e.g., the discriminatory power of the success function and prize allocation scheme) in a nested Tullock contest, they assume the actual number of participants is always concealed to all participants. In contrast, both Fu and Lu (2010) and Kaplan and Sela (2010) assume endogenous entry, however, the number of entrants is always known to all participants.

[6] Our paper is also related to the literature on auctions with entry. The experimental studies include Dyer et al. (1989), Ivanova-Stenzel and Salmon (2004), Palfrey and Pevnitskaya (2008), Isaac et al. (2012) and Aycinena and Rentschler (2018). For a detailed theoretical literature review on auctions with exogenous stochastic entry and endogenous entry, see Boosey et al. (2020).

seems to be in line with our findings because the marginal cost of filling online application forms is likely to be concave. Similarly, a politician seeking to maximize campaign donations may prefer to conceal the number of donors (who expect a political prize for donating after the politician is elected), especially when raising additional funds becomes more expensive. Whether the contest organizers can take advantage the disclosure policy depends on commitment power they have. While the politicians' preference for a disclosure policy may be irrelevant given lobbying activities are often regulated by law, companies may utilize public announcements, third-party certification, or institutional settings on online platforms to gain credibility while enforcing the desired disclosure policy.

2. The model and predictions

We consider a Tullock contest in a three-stage framework. A fixed pool of $M(\geq 2)$ risk-neutral potential participants show their interest in joining the contest with a winner purse $V > 0$. In the preliminary stage, the contest organizer chooses and commits to her information-disclosure policy denoted by $d \in \{D, C\}$, with D and C denoting the full *Disclosure* policy and the full *Concealment* policy, respectively. In Stage 1, after observing the rules of the contest, the potential participants simultaneously decide whether or not to enter the contest. Each participating contestant pays a fixed cost $\Delta > 0$ for entry. Following Anderson and Stafford (2003) and Fu et al. (2015), we make the regular assumption $\frac{V}{M} < \Delta < V$ as a sufficient condition to guarantee that potential participants enter the contest stochastically. The actual number of participants is realized and learnt by the organizer. This information is disclosed to the contestants if the organizer had earlier chosen to do so. In Stage 2, $N(1 \leq N \leq M)$ participating contestants choose their level of effort $\mathbf{x}_N = (x_1, x_2, \ldots, x_N)$ to compete for V. A winner is selected and receives V according to the Tullock (1980) contest success function. Therefore, the winning probability of a participating contestant i is given by

$$p_{i,N}(x_i, \mathbf{x}_{-i}) = \frac{x_i^r}{\sum_{j=1}^{N} x_j^r}, \text{ if } N \geq 2 \text{ and } \sum_{j=1}^{N} x_j^r > 0. \tag{1}$$

By exerting an effort of x_i, contestant i incurs a cost of $c(x_i) = x_i^\alpha$, with $\alpha > 0$. The parameter $r \in (0, \bar{r}] \subset (0, \alpha \frac{M}{M-1}]$ conventionally represents the discriminatory power of the selection mechanism, with $\bar{r}$ as the upper limit imposed to guarantee the existence of a pure-strategy equilibrium effort. A higher r indicates that one's win depends more on his level of effort than on other noisy factors. When there is only one participant entering, he automatically receives the prize V regardless of his level of effort. If more than one contestant enters, but all of them make zero effort, the winner is randomly chosen from the pool of participating contestants. In the case when nobody enters, the organizer withdraws the prize.

Note that given the number of participating contestants, our model with non-linear cost of effort is isomorphic to a contest with linear cost and appropriately adjusted discriminatory power examined by Fu et al. (2011). Let $y_i = x_i^\alpha$ be the *expenditure* of participant i and let $f(y_i) = y_i^{\frac{r}{\alpha}}$. Then the ($N$-player) contest can be framed in terms of expenditure, with contest success function

$$p_{i,N}(y_i, \mathbf{y}_{-i}) = \frac{y_i^{\frac{r}{\alpha}}}{\sum_{j=1}^{N} y_j^{\frac{r}{\alpha}}}, \text{ if } N \geq 2 \text{ and } \sum_{j=1}^{N} y_j^{\frac{r}{\alpha}} > 0.$$

The log-concavity of function $f(y_i)$, together with the discriminatory power $\frac{r}{\alpha} \in (0, \frac{M}{M-1}]$ guarantee the existence and uniqueness of symmetric pure strategy equilibrium in the contest stage.

When policy D is implemented, all contestants know N before deciding on their level of effort. The two-stage subgame boils down to a standard symmetric N-player contest (in Stage 2) with endogenous entry (in Stage 1). Whenever $N \geq 2$, each participant i chooses his level of effort x_i to maximize his expected payoff

$$\pi_i = p_{i,N}(x_i, \mathbf{x}_{-i})V - x_i^\alpha, \tag{2}$$

which is equivalent to choosing expenditure y_i to maximize

$$\pi_i = p_{i,N}(y_i, \mathbf{y}_{-i})V - y_i.$$

As shown by Fu et al. (2011), with characteristic function $H(y) \equiv \frac{f(y)}{f'(y)}$, the corresponding symmetric pure-strategy equilibrium expenditure is $y_N^* = \frac{N-1}{N^2}\frac{rV}{\alpha}$. Therefore, the symmetric pure-strategy Nash equilibrium effort can be written as $x_N^* = \left(\frac{N-1}{N^2}\frac{rV}{\alpha}\right)^{\frac{1}{\alpha}}$, which leads to an expected equilibrium payoff of $\pi_N^* = \frac{V}{N}\left(1 - \frac{N-1}{N}\frac{r}{\alpha}\right)$.[7]

Following the standard argument for games with endogenous entry (Levin and Smith, 1994), each contestant participates if and only if his expected payoff offsets the entry cost. Hence, the unique symmetric subgame perfect equilibrium entry

[7] This symmetric pure-strategy Nash equilibrium can also be obtained by using the standard technique, we relegate the details to Appendix B.

probability $q_D^* \in (0,1)$ in Stage 1 should solve the following equation:[8]

$$\sum_{N=1}^{M} C_{M-1}^{N-1} q_D^{*N-1} (1-q_D^*)^{M-N} \pi_N^* = \Delta, \tag{3}$$

where $C_{M-1}^{N-1} q_D^{*N-1} (1-q_D^*)^{M-N} \pi_N^*$ is the expected payoff of a representative participant who enters the contest, while another $N-1$ contestants enter at the same time.

Given the equilibrium entry probability (q_D^*), the expected total effort (TE_D) is given by

$$TE_D^*(q_D^*) = Mq_D^* \sum_{N=1}^{M} C_{M-1}^{N-1} q_D^{*N-1} (1-q_D^*)^{M-N} \left(\frac{N-1}{N^2} \frac{rV}{\alpha} \right)^{\frac{1}{\alpha}}. \tag{4}$$

When policy C is implemented, N remains unknown to all participants in the two-stage subgame (after the preliminary stage). Therefore, no proper subgame exists after the entry stage and the subgame perfect equilibrium does not bite. Each participant chooses his level of effort after entry based on his (rational) belief about others' entry strategies, without knowing the actual number of entrants.

In this case, the strategy of each potential contestant is given by a pair $(q_{i,C}, x_{i,C})$, where $q_{i,C}$ is the entry probability of a potential participant i and $x_{i,C}$ is his effort upon entry. The symmetric equilibrium has been derived by Fu et al. (2015), which can be summarized as follows: there exists a unique symmetric perfect Bayesian equilibrium, in which each potential contestant enters with a probability q_C^* that uniquely solves the following equation:

$$\sum_{N=1}^{M} C_{M-1}^{N-1} q_C^{*N-1} (1-q_C^*)^{M-N} \frac{V}{N} \left(1 - \frac{N-1}{N} \frac{r}{\alpha} \right) = \Delta\ , \tag{5}$$

and (upon entry) chooses a level of effort x_C^* given by $x_C^* = [\sum_{N=1}^{M} C_{M-1}^{N-1} q_C^{*N-1} (1-q_C^*)^{M-N} \frac{N-1}{N^2} \frac{rV}{\alpha}]^{\frac{1}{\alpha}}$.[9] The expected total effort (TE_C) elicited by the contest organizer is

$$\begin{aligned} TE_C^*(q_C^*) &= Mq_C^* x_C^* \\ &= Mq_C^* [\sum_{N=1}^{M} C_{M-1}^{N-1} q_C^{*N-1} (1-q_C^*)^{M-N} \frac{N-1}{N^2} \frac{rV}{\alpha}]^{\frac{1}{\alpha}}. \end{aligned} \tag{6}$$

We are now able to compare the two equilibrium outcomes to explore the optimal disclosure policy. First, by directly comparing Equations (3) and (5), which are essentially the same, we can derive the following prediction.

Prediction 1 *In a Tullock contest with costly endogenous entry, the equilibrium entry probability of the potential contestants does not depend on the disclosure policy, i.e.,* $q_D^* = q_C^* = q^*$.

Given that the entry probability should not vary with the disclosure policy, the comparative statics on total effort is the same as when entry is stochastic and exogenous. As shown by Fu et al. (2011) in Theorem 1(b), if $H(y)$ is linear, expected equilibrium *expenditure* y is invariant to the disclosure rule. In our model, $H(y) \equiv \frac{f(y)}{f'(y)} = \frac{\alpha}{r} y$ is indeed linear. Applying the inverse of effort-to-expenditure transformation $x^* = (y^*)^{\frac{1}{\alpha}}$, the expected total effort corresponding to the expenditure level must vary with the disclosure policy, in a direction that depends on whether $\alpha \gtrless 1$. According to Jensen's inequality, by further comparing the solutions of Equations (4) and (6), we can summarize the following.

Prediction 2 *In a Tullock contest with costly endogenous entry: (a) concealing the actual number of contestants leads to an expected total effort that is strictly greater (lower) than disclosing the actual number of contestants if and only if the cost function is strictly convex (concave); (b) (Disclosure Irrelevance) the expected total effort is independent of the prevailing disclosure policy when the cost function is linear. That is,* $TE_C^* \gtreqless TE_D^*$ *if and only if* $\alpha \gtreqless 1$.

Similar to Fu et al. (2011), the intuition behind this prediction is the following: Under the *Disclosure* policy, the equilibrium effort of each contestant depends on the cost function (α) and the number of contestants (N), given that $x_N^* = \left(\frac{N-1}{N^2} \frac{rV}{\alpha} \right)^{\frac{1}{\alpha}}$. For a given α, a contestant exerts more effort when N is small, while he exerts less effort when N is large. When the cost function is concave, the equilibrium effort is convex with respect to $\frac{N-1}{N^2} \frac{rV}{\alpha}$. Consequently, effort exertion becomes increasingly elastic when N increases, such that a contestant is more sensitive to any decrease in N (while stepping up effort) than any increase in N (while decreasing effort). Therefore, each contestant, on average, exerts more effort when N is disclosed than when it is concealed. On the contrary, when the cost function is convex, the equilibrium effort becomes concave with respect to $\frac{N-1}{N^2} \frac{rV}{\alpha}$. When N is disclosed, a contestant responds more sensitively to an increase

[8] We recognize that there may exist asymmetric equilibrium entry strategies, i.e., some contestants may participate with a positive probability, while others may never enter. However, given that participants are ex-ante symmetric, following the mainstream literature, we only focus on the symmetric equilibrium in the main text. Detailed discussions about multiple equilibria and asymmetric equilibrium strategies are relegated to Appendix B.

[9] We also relegate the detailed proof of the unique symmetric equilibrium to Appendix B.

Table 1
Treatment design and theoretical predictions.

Treatment		Entry Rate	Individual Effort		TE	TCE	TRD
			N	Value			
Concave	Disclosed 2/3	0.42	$N=0$	0.00	181.98	30.13	0.80
			$N=1$	0.00			
			$N=2$	229.27			
			$N=3$	192.45			
	Concealed 2/3	0.42	-	117.97	147.79	30.13	0.80
Linear	Disclosed 1	0.50	$N=0$	0.00	27.36	27.36	0.88
			$N=1$	0.00			
			$N=2$	25.00			
			$N=3$	22.22			
	Concealed 1	0.50	-	18.12	27.36	27.36	0.88
Convex	Disclosed 4/3	0.56	$N=0$	0.00	11.80	24.29	0.91
			$N=1$	0.00			
			$N=2$	9.01			
			$N=3$	8.25			
	Concealed 4/3	0.56	-	7.42	12.46	24.29	0.91

in N (by lowering effort) than to a decrease in N (by stepping up effort). As a result, his overall expected effort is higher when the number of contestants is concealed.[10]

Another inference that directly follows from Prediction 1 is that the total cost of effort and thus the rent-dissipation rate are also insensitive to the disclosure policy. As each potential contestant receives zero net expected payoff in equilibrium, the total cost of effort of all participants should be exactly equal to the total prize value earned by all potential participants minus the total cost of entry. When all contestants enter with the same probability q^*, the expected total prize earned by all potential participants is $[1-(1-q^*)^M]V$, while the expected total cost of entry is $Mq^*\Delta$.[11] Therefore, the total cost of effort TCE should be the same under both policies

$$\begin{aligned} TCE_D &= TCE_C \\ &= [1-(1-q^*)^M]V - Mq^*\Delta. \end{aligned} \tag{7}$$

The total rent-dissipation rate can be calculated as the ratio of the sum of total cost of effort and total entry cost to the prize value, therefore the two policies will lead to the same level of rent dissipation. We have the following prediction.

Prediction 3 *In a Tullock contest with costly endogenous entry, both the (expected) total cost of effort and the rent dissipation rate are the same under both disclosure policies.*

3. Experimental design and procedure

We design a 2×3 between-subjects experiment that closely follows the theoretical framework described in Section 2. In one dimension, we vary the disclosure policy, i.e., whether the actual number of contestants (N) is disclosed after the entry stage. In the other dimension, we set the curvature of the cost of effort function to be concave (α=2/3), linear (α=1), or convex (α=4/3). We use a lottery contest success function (i.e., $r=1$) to make the winning probabilities easier for the experimental participants to understand. Table 1 summarizes this 2×3 design, with treatment labels, the predicted values of entry rate, individual effort, total effort (TE), total cost of effort (TCE), and total rent dissipation rate (TRD) in each treatment. We conducted two sessions for each treatment with 24 participants per session (except the two sessions for *Conceal 1*, involving 18 and 30 participants respectively).

Printed instructions (See Appendix A for an example) were provided and read aloud by the experimenter before the start of each experimental session. To further ensure that all participants understood the instructions correctly, at the beginning of each session they were asked to take a quiz based on the experimental instructions. The participants could only continue if they answered each question correctly. To increase the number of independent observations, participants (in each session) were first randomly assigned to two (sub)session groups, which remained the same for the entire experiment. The size of the (sub)session groups was 9, 12, or 15 respectively. Any subsequent random matching was conducted at this (sub)session level.

Each session ran for 25 rounds. At the beginning of each round, the participants were randomly assigned to a group of three players, each receiving 80 experimental currency (EC) units as their initial endowment. In Stage 1, the participants simultaneously decided whether to enter. An entry fee of 40 EC was deducted from their initial endowment if they decided

[10] In Appendix B, We also provide more detailed calculations and graphical representations for a simplest two-player case (i.e., $M=2$) to further illustrate how the comparisons described in Prediction 2 can be simply proved using Jensen's Inequality.

[11] Note that $(1-q^*)^M$ is the probability that nobody enters the contest, thus the prize is kept by the organizer, and $1-(1-q^*)^M$ is the probability that the prize is taken by one participant.

Table 2
Average entry rates and equilibrium predictions.

	Concave		Linear		Convex	
	Equ.	Rd.1–25	Equ.	Rd.1–25	Equ.	Rd.1–25
Disclosure	0.42	0.69 (0.46)	0.50	0.60 (0.49)	0.56	0.59 (0.49)
Concealment	0.42	0.62 (0.49)	0.50	0.59 (0.49)	0.56	0.63 (0.48)

Standard deviations are reported in brackets. The columns labeled "Equ." provide the equilibrium entry probabilities. Columns "Rd.1-25" show the summary statistics of observations from all 25 rounds.

to enter. Those who did not enter kept their 80 EC as their payoff for the round, and were not allowed to participate in Stage 2. After all participants made their entry decisions, the actual number of entrants (N) was revealed (concealed) to all participants in the disclosed (concealed) treatments, including those who did not enter.[12] In Stage 2, all entrants chose their level of effort, x, to compete in the contest with a single prize worth 100 EC. Their level of effort was then converted into cost and deducted from their remaining endowment (i.e., 40 EC). The participants were given a table listing all available levels of effort (and their corresponding cost), as well as a graph showing the curvature of the cost function. Depending on the cost function used in the treatment, the range of effort levels varied and was bounded by the remaining endowment after entry fee is deducted (i.e., 40 EC).[13]

After all of the entrants made their effort choices, a winner was randomly selected from each contest group according to the lottery contest success function. An animated lottery wheel was used to show the process of the random draw. Once a winner was determined, all group members received full feedback information, including all group members' entry and effort choices, their corresponding winning probabilities, the outcome of the random draw, and their own payoff for this round. One of the 25 rounds was then randomly chosen by the computer at the end of each session for payment calculation. The EC earned during selected round were converted to RMB at a rate of 3.2 EC = RMB 1. The participants earned RMB 40 on average (including RMB 15 as a show-up fee) and each session lasted approximately one hour.[14] The experiment was programmed and run by z-Tree (Fischbacher, 2007). All 288 participants were undergraduate or postgraduate students in Wuhan University in the winter of 2017. At the end of each experimental session, a standard questionnaire was used to collect demographic information (such as age, sex, study major, etc.).

4. Results

In this section, we first compare the average entry rate, the average total effort and total cost across disclosure policies to test the main predictions presented in Section 2. We then examine the individual effort choices and compare them with the equilibrium predictions. Unless otherwise specified, we always refer "treatment effect" to the comparison between the *Disclosed* treatment and the *Concealed* treatment under the same cost-of-effort function.

4.1. Entry rate

Table 2 summarizes the average entry rates (with standard deviations in brackets) for each treatment, in contrast with their corresponding equilibrium predictions. The average entry rates are generally higher than the equilibrium predictions. When the cost function is concave, given a predicted entry probability of 42%, over-entry is more prominent (69% and 62% under the *Disclosure* and *Concealment*, respectively). When the cost of effort is linear, over-entry is moderate (60% and 59% against 50% in the predictions). When the cost function is convex, over-entry is the lowest (59% and 63% against 56% in the predictions).

We further use regression analysis with multi-level mixed-effects models to control for the random effects at the (sub)session and individual levels. Both linear and logistic regressions are presented in Table 3. The average entry probabilities are not significantly different across the *Disclosure* and the *Concealment* policies for all cost structures (see the coefficients of the treatment dummy "Concealed" in columns 2 to 4). Over-entry is slightly corrected from rounds 1–13 to rounds 14–25 in both treatments with a concave cost when over-entry is the greatest (see the coefficient for "2nd_half" in column 5). After controlling for the learning effect, the treatment effect remains insignificant under all cost structures. These results on entry behavior remain unchanged in Model 3 when we add control variables and in Model 4 when multi-level mixed-effects logistic regressions are used.[15] Similar to the previous studies, our data also suggest that those who claimed

[12] By informing those who did not enter, we kept information and learning relatively symmetric between participating and non-participating players.

[13] This corresponds to a range of effort levels from 0 to 40 when the cost function is linear, 0 to 253 when it is concave, and 0 to 15.9 when it is convex. We allowed participants to enter decimal points in their effort choices in all treatments so that the coarseness of the strategy space is more comparable across treatments.

[14] This average payment was equivalent to the hourly rate paid to a university research assistant in that region when the experiment was conducted.

[15] Neither gender nor study background significantly affects the entry behavior (see coefficients for the "Male" and "Major" dummies in Table 3.

Table 3
Entry behavior: Regression analysis.

	Mixed Linear Regression									Mixed Logit Regression		
	Model 1			Model 2			Model 3			Model 4		
VARIABLES	Concave	Linear	Convex	Concave	Linear	Convex	Concave	Linear	Convex	Concave	Linear	Convex
Constant (Disclosed)	0.69***	0.60***	0.59***	0.72***	0.62***	0.59***	0.34***	0.35***	0.29***	−1.59*	−1.05	−1.46**
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.11)	(0.09)	(0.09)	(0.84)	(0.72)	(0.64)
Concealed	−0.07	−0.02	0.04	−0.07	−0.02	0.06	−0.03	−0.02	0.05	0.05	−0.32	0.26
	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.05)	(0.06)	(0.47)	(0.43)	(0.39)
2nd_half				−0.06***	−0.03	−0.01	−0.05**	−0.03	−0.01	−0.36**	−0.20	−0.06
				(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.16)	(0.16)	(0.15)
Concealed X 2nd_half				−0.00	0.00	−0.04	−0.00	0.01	−0.03	−0.08	0.12	−0.18
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.24)	(0.23)	(0.21)
Risk							0.06***	0.07***	0.07***	0.50***	0.53***	0.43***
							(0.01)	(0.01)	(0.011)	(0.10)	(0.09)	(0.08)
Male							−0.03	−0.06	−0.01	−0.03	−0.39	0.18
							(0.06)	(0.05)	(0.05)	(0.48)	(0.41)	(0.33)
Win_t-1							0.12***	0.14***	0.12***	0.94***	0.93***	0.79***
							(0.02)	(0.02)	(0.02)	(0.15)	(0.13)	(0.13)
Major							0.03	−0.10	−0.03	0.18	−0.77	−0.13
							(0.07)	(0.07)	(0.07)	(0.56)	(0.54)	(0.49)
$\sigma^2_{(sub)session}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.06
	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.00)	(0.00)	(0.00)	(0.18)	(0.14)
$\sigma^2_{individual}$	0.95	0.98	0.08	0.948	0.984	0.084	0.07	0.05	0.05	4.17	2.94	2.04
	(0.01)	(0.15)	(0.13)	(0.01)	(0.02)	(0.13)	(0.01)	(0.01)	(0.01)	(0.88)	(0.65)	(0.44)
Observations	2400	2400	2400	2400	2400	2400	2400	2400	2400	2304	2304	2304
Number of groups	8	8	8	8	8	8	8	8	8	8	8	8

We run multi-level mixed-effects regressions on binary entry choices as a function of the treatment dummy ("Concealed") in Model 1, controlling for the random effects at both the individual and the (sub)session levels. The *Disclosed* treatment under each cost structure is used as the baseline category. In Model 2, we add a time-specific dummy variable (2nd_half) to identify learning from rounds 1–13 to rounds 14–25, and further add control variables that may affect the participants entry decisions in Model 3. In model 4, we provide logistic regressions as a robustness check. "Risk" is a self-reported measure of willingness to take risks in everyday life, which takes integers between 0 and 10, with 0 being "Not willing to take risks at all" and 10 being "Very willing to take risks." "Win_{t-1}" is a binary variable that is equal to 1 if the participant won in the previous round, and 0 otherwise. "Major" is a dummy variable that equals to 0 for participants who study science, engineering, mathematics or economics, and 1 for the remaining areas (e.g., arts, history, literature, or law). All standard errors are reported in brackets. Stars indicate the significance level (i.e., $^{**}p < 0.05$, $^{***}p < 0.01$).

to be more risk-loving entered more frequently, and those who won in the previous round were more likely to join the contest in the next round.

We then test the estimated average entry rates against their corresponding equilibrium predictions to establish the significance of the differences between the actual entry probabilities and the equilibrium predictions. Over-entry is significant in all treatments with the concave cost function at the 1% level even if we only examine the entry choices in rounds 14–25, but not significant at the conventional 5% level in other treatments with a linear or convex cost.[16]

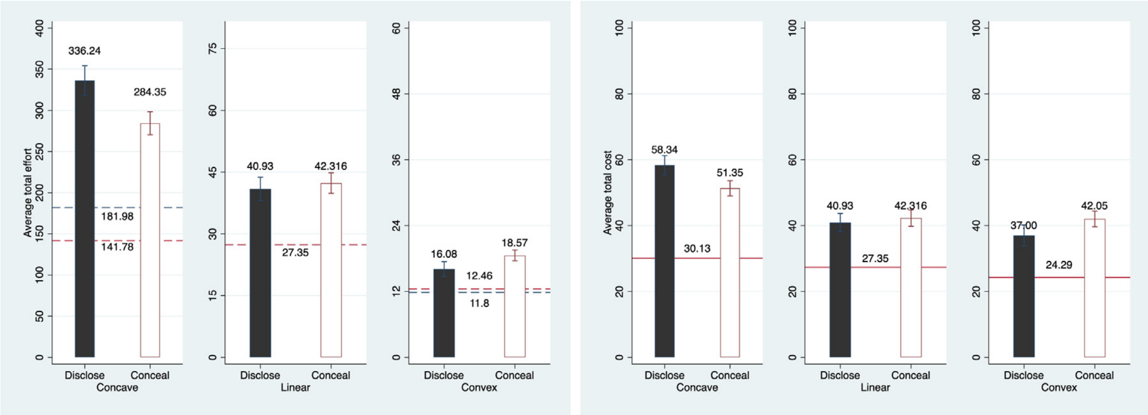
Result 1 *The entry behavior of potential participants is largely invariant to the disclosure policies, whether the cost of effort is concave, linear, or convex.* (supporting Prediction 1)

4.2. Total effort and total cost

After examining the average entry rates across the disclosure polices, we compare the average total effort to identify the optimal disclosure policy a contest organizer should adopt. The average total effort, which is calculated as the aggregate effort made by each three-player contest group averaged across all contest groups within a sub(session) in one round, is taken as the unit of observation in this part of the analysis. Figure 1a presents the summary statistics of the average total effort. The corresponding equilibrium predictions are also represented by the dashed lines. Figure 1a suggests that the differences between the *Disclosure* and *Concealment* policies follow the direction of the theoretical predictions, although the average total effort is generally higher than the equilibrium predictions. When the cost function is concave, the average total effort is 18% higher under the *Disclosure* policy than under the *Concealment* policy (336.24 vs. 284.35). In contrast, when the cost of effort is convex, the average total effort in the disclosed treatment is 13% lower than that of the concealed treatment (16.08 vs. 18.57). When the cost function is linear, the difference between treatments is the smallest of all (40.93 vs. 42.32).

We again estimate the mixed-effects models to control for the random effects at the (sub)session level, and thereby to further test the significance of the treatment effects. The regression results are presented in Table 4. In the concave- and linear-cost cases, the regression results further confirm what we observe in Fig. 1 a: the average total effort is significantly lower under the *Concealment* policy when the cost function is concave ($p = 0.036$), and is not significantly different across

[16] The p values are 0.00 and 0.00 for the concave case, 0.07 and 0.14 for the linear case, and 0.58 and 0.35 for the convex case, based on Wald tests.



(a) Average total effort (b) Average total cost

Fig. 1. A summary of the average total effort and the average total cost, in contrast to their equilibrium predictions.

Table 4
Total Effort: Mixed-effects Models.

	Model 1			Model 2		
	Concave	Linear	Convex	Concave	Linear	Convex
Constant (Disclosed)	336.24***	40.93***	16.08***	357.09***	45.12***	16.22***
	(17.46)	(2.13)	(1.40)	(18.74)	(2.43)	(1.49)
Concealed	−51.89**	1.38	2.49	−53.61**	−0.18	3.09
	(24.70)	(3.01)	(1.98)	(26.51)	(3.44)	(2.11)
2nd_half				−43.44**	−8.73***	−0.31
				(14.17)	(2.46)	(1.06)
Concealed× 2nd_half				3.59	3.25	−1.27
				(20.05)	(3.48)	(1.50)
$\sigma^2_{(sub)session}$	1,001.42	11.49	6.73	1,019.49	12.04	6.74
	(610.39)	(9.07)	(3.93)	(610.39)	(9.07)	(3.93)
Obs	200	200	200	200	200	200
No. of groups	8	8	8	8	8	8

We compare the average total effort across disclosure policies by regressing the average total effort on the disclosure policy dummy ("Concealed") for different cost functions separately in Model 1. In Model 2, we add a time-specific dummy (2nd_half) that is equal to 1 for rounds 14–25. We use mixed-effects regressions to control for the random effects at the (sub)session level. Stars indicate the significance level ($^{**}p < 0.05$, $^{***}p < 0.01$).

disclosure policies when the cost function is linear ($p = 0.70$). In the convex-cost case, although the direction of the effect is in line with the theoretical prediction, it is not statistically significant ($p = 0.21$). These results remain consistent even after we add a time dummy to control for the potential learning effect (see Model 2 in Table 4).

Result 2 *In line with the theoretical prediction, the average total effort is significantly higher under the* Disclosure*policy than under the* Concealment*policy when the cost of effort function is concave, and it is insensitive to the disclosure policy when the cost of effort is linear. The treatment difference also follows the direction predicted by the theory when the cost function is convex, although it is not statistically significant.* (partially supporting Prediction 2)

Note that *Prediction 3* also states that the total cost of effort should be invariant to the disclosure policies, and the same applies to the rent-dissipation rate. Similarly, We take the average total cost (of effort) that is calculated in the same way as the average total effort, as one unit of observation. Figure 1b summarizes the average total cost of effort for each treatment. The solid lines represent the corresponding equilibrium predictions. In general, moderate levels of over-dissipation occur across all treatments (in line with the higher than equilibrium levels of total effort), yet the treatment effects seem small for all cost structures.

Following the same investigation logic as the average total effort, we run mixed-effects regressions, controlling for random effects at the (sub)session group level for the average total cost. The results are presented in Table 5. In line with the theoretical predictions, we find that the average total costs are not significantly different across disclosure policies when the cost function is linear and convex ($p = 0.46$ and $p = 0.28$, respectively). When the cost function is concave, the difference is marginally significant in Model 1 ($p = 0.065$). However, after controlling for the learning effect by adding a time-

Table 5
Total Cost: Mixed-effects Models.

	Model 1			Model 2		
VARIABLES	Concave	Linear	Convex	Concave	Linear	Convex
Constant (Disclosed)	58.34***	40.93***	37.01***	62.02***	45.12***	37.21***
	(2.68)	(2.13)	(3.30)	(2.90)	(2.43)	(3.52)
Concealed	−6.99	1.38	5.04	−7.26	−0.18	6.71
	(3.79)	(3.01)	(4.66)	(4.10)	(3.44)	(4.97)
2nd_half				−7.66***	−8.73***	−0.41
				(2.33)	(2.46)	(2.54)
Conceal × 2nd_half				0.57	3.25	−3.48
				(3.29)	(3.49)	(3.59)
$\sigma^2_{(sub)session}$	22.72	11.49	36.99	23.29	12.04	37.07
	(14.36)	(9.08)	(21.77)	(14.36)	(9.07)	(21.77)
Obs	200	200	200	200	200	200
No. of sub-sessions	8	8	8	8	8	8

We compare the average total cost across disclosure policies by regressing the average total cost on a disclosure policy dummy ("Concealed") for each cost function separately in Model 1. In Model 2, we add a time-specific dummy (2nd_half) equal to 1 for rounds 14–25. We use mixed-effects regressions to control for the random effects at the (sub)session level. Stars indicate the significance level (** $p < 0.05$, *** $p < 0.01$).

specific dummy in Model 2, we find that the difference becomes insignificant in rounds 14–25 at all conventional levels ($p = 0.107$).[17]

Result 3 *In line with Prediction 3, the average total cost is invariant to the disclosure policies under all cost structures after some learning from the early rounds (1–13).* (Supporting Prediction 3)

The total cost spent by the contestants is essentially borne by the contest organizer, as the total cost of effort spent by the participants offsets the prize value provided by the organizer. Integrating the results on the average total effort and the average total cost, our study suggests that if the objective of a contest organizer is to maximize or minimize the total effort while maintaining the cost of the contest, she should select the disclosure policy after carefully considering the nature of the effort-cost function. When the cost of effort is expected to be concave, fully disclosing the actual number of contestants is expected to be more effective in eliciting higher total effort. Naturally, if the objective of the contest organizer is to minimize the expected total effort, the optimal policy is the opposite. When the cost of effort is expected to be linear, the disclosure policy is irrelevant, as the expected total effort and the expected total cost are both unresponsive to the disclosure policy. When the cost of effort is expected to be convex, our data may lack power in detecting the treatment effect, but ignoring the predicted differences across disclosure policies based on our theoretical model may be sub-optimal.

4.3. Individual effort

The participants in the *Disclosed* and *Concealed* treatments make their effort choices under different levels of information. In the *Disclosed* treatments, they know how many people they are competing against, while in the *Concealed* treatments, this information is not available, thus they must form a belief on the entry strategy of other people. In the former case, the equilibrium effort choices change with the actual number of entrants. We first compare the individual efforts exerted in different cases (i.e., $N = 1$, 2, or 3) in the *Disclosed* treatments to see if they follow the equilibrium predictions. In the latter case, not knowing the actual number of entrants, the contestants are predicted to make the same level of effort across different sizes of contests. We then check if this is true and also compare the actual effort choices with the corresponding equilibrium predictions.

Table 6 reports the average individual efforts in each of the three *Disclosed* treatments, conditional on the actual number of entrants, in contrast with the corresponding equilibrium predictions. When the participants enter the contest alone ($N = 1$), they should make 0 effort in all three treatments, as the prize is automatically awarded to them. The summary statistics show that some participants still make positive efforts, which may be driven by some confused participants not fully understanding the rule of the contest at the beginning. Multi-level mixed-effects regressions using data from rounds 14–25 to study the choice of the participants after learning show that the average effort in this case is noisy and not significantly different from 0 (See Table 7, row "$N = 1$").

When more than one contestant enters the contest, their effort choices are in line with the equilibrium predictions when the cost function is linear (comparing columns 4 and 5 in Table 6). Similarly, mixed-effects regressions using data from the last 12 rounds provide estimates that are not significantly different from the equilibrium predictions (see Table 7 column 3).

When the cost function is non-linear, we observe that the individual effort is slightly lower than the equilibrium predictions when the cost function is concave (197.48 vs. 229.27 when $N = 2$, and 156.05 vs. 192.45 when $N = 3$). However,

[17] To test the difference in rounds 14–25, we conduct a post-estimation test by comparing the sum of the regression coefficients of the treatment dummy (Concealed) and the interaction term (Concealed × 2nd_half) with zero.

Table 6
Individual Effort in Disclosed Treatments.

	Concave		Linear		Convex	
	Equ.	Rd.1–25	Equ.	Rd.1–25	Equ.	Rd.1–25
$N = 1$	0	23.33	0	5.02	0	0.86
		(70.62)		(11.85)		(3.19)
$N = 2$	229.27	197.48	25	26.76	9.01	11.64
		(63.33)		(10.39)		(3.95)
$N = 3$	192.45	156.05	22.22	24.33	8.25	9.91
		(79.11)		(12.06)		(4.59)

Standard deviations are reported in brackets. The columns labeled "Equ." provide the equilibrium predictions. "Rd.1-25" show the summary statistics of observations from all 25 rounds.

Table 7
Individual Effort in Disclosed Treatments: Rounds 14–25.

	Mixed-effects model			Tobit model		
	Concave	Linear	Convex	Concave	Linear	Convex
$N = 1$	12.73	1.42	0.73			
	(16.17)	(1.79)	(0.58)			
$N = 2$	198.80**	25.93	12.07***	242.60	28.49	13.22***
	(13.10)	(1.54)	(0.50)	(29.92)	(2.85)	(0.80)
$N = 3$	157.00***	22.63	9.57**	183.90	24.56	10.34**
	(13.01)	(1.64)	(0.51)	(29.62)	(2.92)	(0.81)
$\sigma^2_{(sub)session}$	450.65	4.06	0.00	2810	16.64	0.00
	(452.61)	(6.28)	(0.00)	(2483)	(22.61)	(0.00)
$\sigma^2_{individual}$	1,506.05	35.90	7.57	5062	125.8	22.28
	(448.04)	(11.48)	(1.94)	(1626)	(38.92)	(6.01)
Censored				[10, 113]	[4, 60]	[3, 65]
Total Obs.	379	340	337	344	278	274

"Censored" represents the number of observations that are left-censored (first number in brackets) and right-censored (second number in brackets). We control for the random effects at the individual level ($\sigma^2_{individual}$) and the (sub)session level ($\sigma^2_{(sub)session}$) in the mixed-effects and Tobit models. Note that stars indicate the significance level of the estimated coefficients against their corresponding theoretical predictions using Wald tests (** $p < 0.05$, *** $p < 0.01$). Standard errors are reported in brackets.

when the cost function is convex, the average effort is slightly above the equilibrium predictions (11.64 vs. 9.01 when $N = 2$, and 9.91 vs. 8.24 when $N = 3$). These results suggest that the effort choices respond to the curvature of the cost function in the right direction, although the reactions are slightly smaller than those suggested by the theoretical point predictions. Table 7 (columns 2 and 4) shows that these deviations from the equilibrium predictions are statistically significant when using mixed-effects regressions.

The histograms of the individual effort choices presented in Fig. 2 suggest that the effort choices are heterogeneous and often limited by the maximum effort available to the participants. For example, approximately 40% of the choices are distributed at the upper bound (253) when the cost function is concave, and the actual number of contestants is two. In other cases, between 25% and 30% of the choices are distributed at the upper bound.[18] To take into account the impact of the upper bounds on effort choices, we also estimate the average individual effort in each case with multi-level mixed-effects Tobit models, using data from rounds 14–25. The results are presented in Table 7 (columns 5 to 7).[19] As Table 7 shows, the effort choices are not significantly different from the equilibrium predictions when the cost function is concave or linear, while the level of effort remains higher than the equilibrium predictions when the cost function is convex.

Result 4 *The participants' individual effort largely follows the equilibrium predictions when N is disclosed, although the participants slightly under-react to the curvature of the cost function when the cost of effort is non-linear, especially when it is convex.*

Table 8 summarizes the average individual effort, with the standard deviations for each *Concealed* treatment given in brackets. The average individual effort is generally higher than the equilibrium predictions in all treatments when the actual number of contestants is concealed. To compare the individual effort with the equilibrium predictions, we estimate the average individual effort using multi-level mixed-effects models, controlling for the random effects at the individual and

[18] See Appendix C.6 for individual effort plots (for each N) by treatment.

[19] All of the regressions using Tobit models are right-censored at the maximum effort level available to the participants, and left-censored at the minimum level of 0. The case $N = 1$ is left out because most participants choose 0 when nobody competes with them.

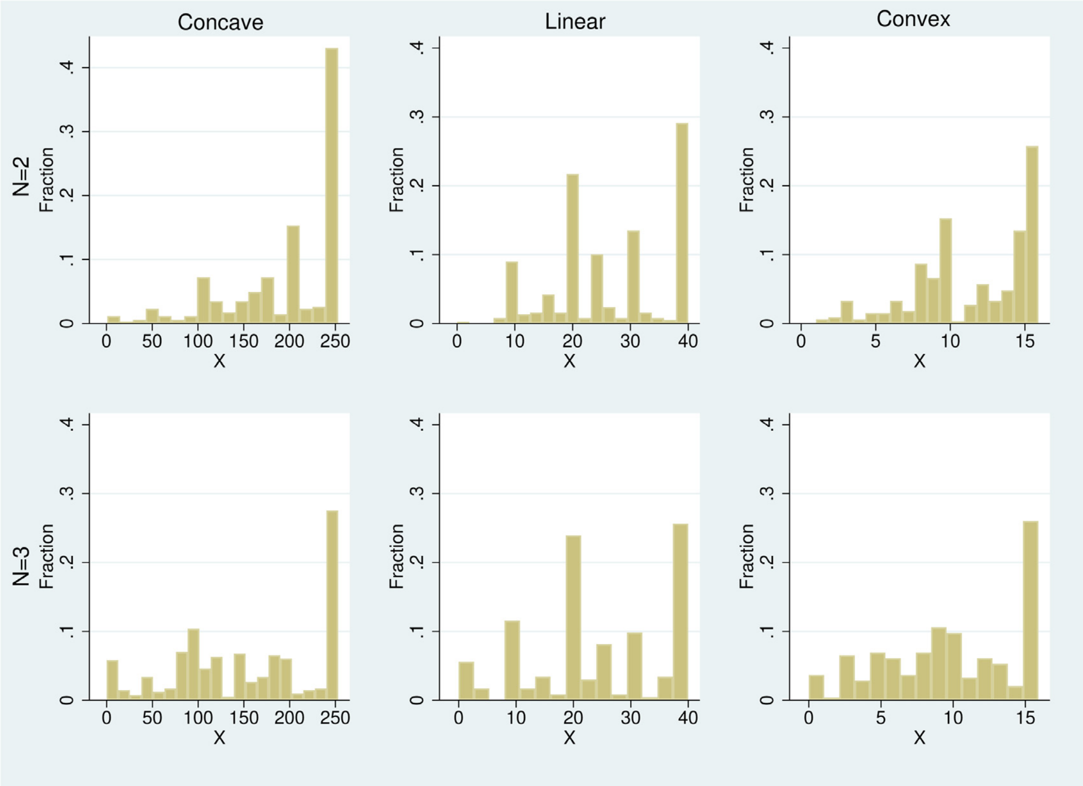


Fig. 2. Histograms of individual effort in Disclosed treatments.

Table 8
Individual Effort in Concealed Treatments.

Concave		Linear		Convex	
Equ.	Rd.1-25	Equ.	Rd.1-25	Equ.	Rd.1-25
117.97	154.12 (71.54)	18.12	23.78 (12.11)	7.42	9.88 (4.59)

Standard deviations are reported in brackets. The columns labeled “Equ.” provide the equilibrium predictions. “Rd.1-25” show the summary statistics of observations from all 25 rounds.

(sub)session levels. The estimates are significantly higher than the equilibrium predictions in all three treatments (p values are 0.00, 0.05, and 0.00, see Fig. 3 for the estimated values).[20]

Under the *Concealment* policy, the participants make effort decisions without knowing the actual number of entrants. They should choose an effort level that maximizes their expected payoff, taking into account the probability distribution of the potential number of opponents they will face.[21] As the actual entry rates are slightly higher than the equilibrium entry rates, the probability distribution of the actual number of opponents they will face also deviates from the equilibrium predictions. Thus, the over-exertion observed under the *Concealment* policy may be a rational reaction to over-entry.

In our experiment, the participants received full feedback at the end of each round, irrespective of whether they entered the contest. As a result, the participants should have a good perception of the actual average entry rates. We conjecture that the over-exertion observed may reflect the best responses of participants to their belief/perception of the actual entry behavior. To further test this conjecture, we calculate the payoff-maximizing effort based on the observed average entry rates using data from rounds 14–25. As shown in Fig. 3, the estimated average individual effort in the concave and linear treatments (155.60 and 22.85) is not significantly different from the optimal effort choices predicted by the actual average entry rates and indicated by the blue dashed lines (160.44 and 19.56, p =0.69 and p = 0.18, respectively). However, when

[20] The full regression results using data from rounds 14–25 can be found in Appendix C.1. The estimated coefficients are similar if we use data from all rounds.

[21] We draw the histogram of individual effort in concealment treatments conditional on cost function and the number of entrants. Participants effort choice does not vary with the number of entrants. See Appendix C for the histograms.

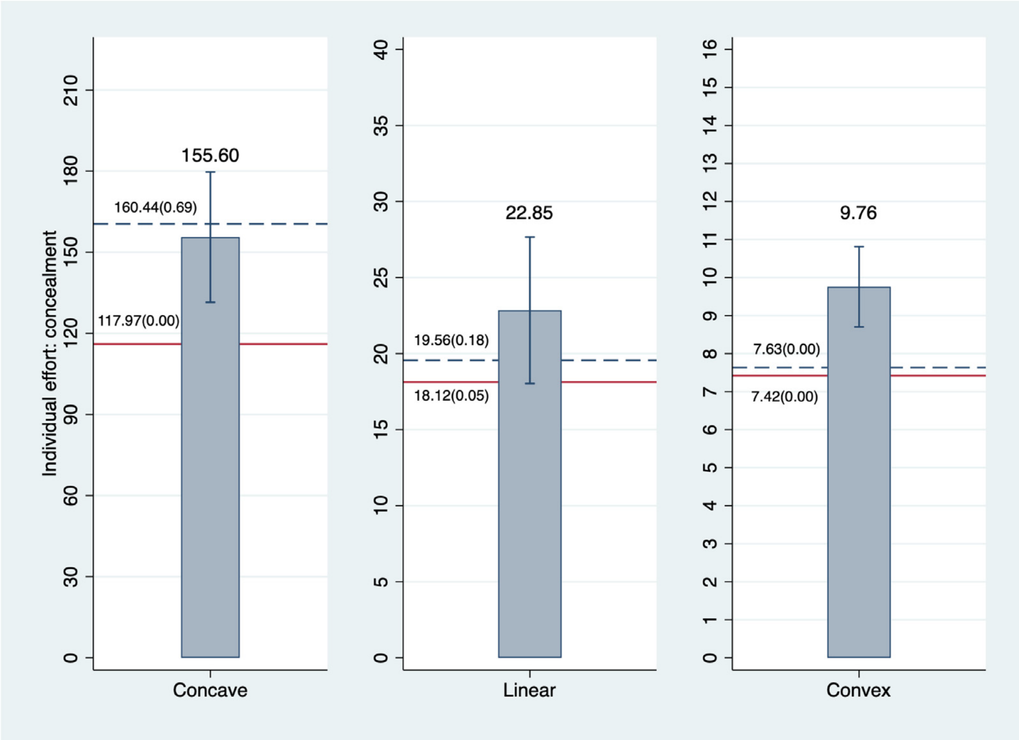


Fig. 3. Individual Effort in Concealed Treatments: Rounds 14–25. *Note:* The red solid lines represent the equilibrium predictions and the blue dotted lines represent the predicted optimal individual effort, taking the actual entry rates as given. The figures in brackets next to the theoretical predictions are the *p*-values of the Wald tests, which compare the estimated coefficients using multi-level mixed-effects models for rounds 14–25 (see the number at the top of each bar) with the predictions adjusted by over-entry.. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the cost of effort is convex, the estimated average effort is still significantly higher than the optimal effort adjusted by over-entry (9.76 vs. 7.63, $p \leq 0.01$).[22]

Result 5 *The participants' individual effort is generally higher than the equilibrium predictions in all treatments when the actual number of contestants is concealed. However, when the over-entry behavior is taken into consideration (i.e., using the actual entry rates observed in the experiment in calculating the payoff-maximizing individual effort), the choices are largely consistent with adjusted optimal effort predictions, except that there is still significant over-exertion in effort when the cost function is convex.*

In summary, our analysis on individual efforts suggests moderate levels of over-exertion when the cost of effort is convex, contrasting the majority of the experimental evidence on contest that shows much higher levels of over-exertion.[23] One could reasonably argue that the closer to equilibrium effort choices observed in our experiment might be driven the fact that the strategy space is bounded by the initial endowment assigned to the participants.[24] As is shown by the Tobit regressions, the strategy space is particularly restrictive under the *Disclosure* policy when the cost of effort is concave, however, it restricts the effort choices to a lesser extent under the *Concealment* policy. Therefore, we speculate that should the participants be allowed to exert higher effort, the treatment difference on the expected total effort would have been more prominent when the cost of effort is concave. When the cost function is convex, the difference in equilibrium-effort predictions across disclosure policies is very small, taking into account the bounded strategy space would be unlikely to drive the treatment effect significantly different.[25] All in all, in spite of the various deviations observed on the individual level of choices, our finding on the treatment effect with regard to the average total effort (summarized in Result 2) remains unchanged.

[22] Note that over-entry is minimal when the cost of effort is convex. Therefore, controlling for over-entry hardly changes the predicted optimal effort compared with the Nash equilibrium prediction (7.63 vs. 7.42).

[23] We have shown that the over-exertion in the concealed treatments (when the cost of effort is either linear or concave) may be driven by individuals best-responding to over-entries in these treatments.

[24] For example, Baik et al. (2020) provide experimental evidence on the impact of conflict budget on the intensity of conflict.

[25] The bounded strategy space is to ensure the entry cost is non-trivial and the endowment is comparable across cost structures. Obviously, restricted strategy space comes as its cost.

5. Conclusion

In this paper, we examine theoretically and experimentally whether it is optimal for a contest organizer to disclose the actual number of contestants when entry is endogenous. Although previous studies suggest that the expected total effort made in a Tullock contest does not depend on the disclosure policy when the cost of effort is linear, we show that the optimal disclosure policy critically depends on the convexity of the cost function when the cost of effort is non-linear, despite the equilibrium entry probabilities and rent dissipation rates are invariant to the disclosure policy.

More importantly, we find that, in line with our theory, the *Disclosure* policy tends to elicit more total effort than the *Concealment* policy when the cost function is concave, and that the total effort is neutral to the disclosure policy when the cost function is linear. When the cost function is convex, the theory predicts that the total expected effort should be higher under *Concealment* policy, and we observe a difference in the direction predicted by the theory. However, it is not statistically significant. The lack of significant treatment difference may be attributed to two factors: first, the predicted treatment effect is rather small, thus it is more difficult to detect with our data; and second, we observe significant over-exertion under both *Disclosure* and *Concealment* policies when the cost function is convex, which makes it even harder to detect small treatment differences.

Our contest model is certainly too stylised to fully capture the complexity of the real-world contests. Nonetheless, it provides useful insights on both the positive and normative aspects of the disclosure policies. Further empirical research is warranted to identify the nature of the cost-of-effort function in practice when a specific real contest is concerned. Once the nature of the cost-of-effort functions is identified, one could answer why in some circumstances the number of contestants is revealed, whereas in others it is concealed. In this paper, we have focused on full disclosure and full concealment policies. Although we expect that our main results can be extended to a more general information disclosure policy framework, new issues related to information disclosure may arise and create additional challenges for analysis. We leave these interesting questions for future work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2015.01.016.

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