Information disclosure in contests with endogenous entry: An experiment

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Abstract

We use a laboratory experiment to study the effects of disclosing the number of active participants in contests with endogenous entry. At the first stage potential participants decide whether to enter competition, and at the second stage active entrants choose their investments. In a 2×2 design, we manipulate the size of the outside option, ω, and whether or not the number of entrants is disclosed between the stages. Theory predicts more entry for lower ω, and the levels of entry and *ex ante* investment to be independent of disclosure in all cases. We find empirical entry frequencies consistent with these predictions. For aggregate investment, we find no effect of disclosure when ω is low, but a strong positive effect of disclosure when ω is high, i.e., when the expected number of entrants is relatively low. The difference is driven by substantial overbidding in contests with a small, publicly known number of players, contrasted by more restrained bidding in contests where the number of players is uncertain and may be small.

Keywords: contest, endogenous entry, information disclosure, experiment
JEL classification codes: C72, C92, D82

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1 Introduction

We study experimentally how interim disclosure of information affects behavior in contests with endogenous entry. Such contests are modeled as a two-stage game where at the first stage participants decide whether to incur a fixed cost and enter the contest, or to stay out, and at the second stage entrants invest in competition for a valuable prize. Our main focus is on the effects of disclosing the number of entrants at the start of the second stage. While there exists a substantial theoretical literature on the consequences and optimality of such disclosure in various contest settings, this paper provides the first empirical test.

Endogenous entry is a natural feature of many, if not most, contest environments, from R&D firms deciding whether or not to enter an innovation race to job candidates deciding whether or not to apply for a position, to athletes deciding whether to enter a particular tournament. These entry decisions can be costly, either in the form of explicit upfront costs and entry or application fees, or in the form of opportunity costs. Importantly, the exact number of entrants may or may not be known to participants at the time of investment. For example, athletes in a sports tournament or R&D firms in a particular industry are typically well aware of their competitors, but often the same cannot be said about job applicants or lobbyists.

The prevalence of endogenous entry in contests in the field provides the basic motivation for our study. However, our main motivation is the fact that endogenous entry without disclosure leads to *group size uncertainty* at the investment stage. Previous work has found that the presence of such uncertainty may have substantial effects on behavior. Specifically, while the existing experimental literature on contests with fixed group size overwhelmingly documents *overbidding*, i.e., investments exceeding the risk-neutral Nash equilibrium predictions, or even investments from a strictly dominated region (Sheremeta, 2013), recent evidence suggests that the overbidding is reduced significantly when group size is unknown and there is a nontrivial probability for a player to be alone in the contest (Boosey, Brookins and Ryvkin, 2017*b*). Therefore, even in settings where, theoretically, disclosing the number of entrants has no effect on aggregate *ex ante* equilibrium investment (Lim and Matros, 2009; Fu, Jiao and Lu, 2011, 2015), empirically, it may have a substantial effect on investment, by way of removing group size uncertainty. If that is the case, our findings should be of interest to contest organizers in various settings where it is the designer's choice whether or not to disclose the number of entrants.[1] For example, pol-

[1] We assume that the contest designer can commit to a disclosure rule in advance. This holds in many settings; for example, various forms of sunshine laws require governments to provide information about job applicants or bidders in procurement auctions. Otherwise, the designer may follow a disclosure strategy that is contingent on the realized number of entrants.

icy makers can withhold, or make publicly available, information about the participants of a procurement auction or candidates for a state university president position.

Our experiment follows a 2×2 between-subject design where we manipulate the outside option (or, equivalently, entry fee) and whether or not the number of entrants is disclosed. We use a canonical winner-take-all symmetric setting where, under certain parameterizations, the symmetric equilibrium involves players mixing between entering and not entering with some probability q^*, and both q^* and *ex ante* equilibrium investment are independent of disclosure. By changing the outside option, ω, we generate treatments with relatively high and low values of q^*, thereby exploring scenarios where, in equilibrium, the probability for a player to be alone in the contest is low or high.

We find the comparative statics for entry frequencies consistent with theory. Moreover, while we observe entry below the equilibrium level when ω is low (q^* is high), and above equilibrium when ω is high (q^* is low), the point estimates for entry frequency are explained very well by the Quantal Response Equilibrium (McKelvey and Palfrey, 1995). For aggregate investment, consistent with the behavioral predictions described above, we find that disclosure has a strong positive effect when ω is high, but not when ω is low. The effect of disclosure for high ω is rather striking considering that when a player is the only entrant, and this information is disclosed, she wins the contest with certainty with zero investment. However, the disclosure-induced overbidding in cases when the number of entrants is greater than one is so high that it more than compensates for these instances of zero investment.

Our results show that institutional commitment to disclosing the number of entrants in all-pay contest environments can have significant welfare implications. Population uncertainty generated by nondisclosure dampens excessive investment. In situations where investment is productive, such as R&D competition or productive effort in organizations in competition for promotion, the contest organizer can benefit from disclosure, especially when the expected number of participants is small. In settings where contest investment is viewed as wasteful spending, such as lobbying, nondisclosure can be beneficial. Concealing the number of entrants may also benefit organizations where competitive incentives tend to generate adverse, counterproductive behaviors, such as sabotage (e.g., Harbring and Irlenbusch, 2011).

The rest of the paper is organized as follows. In Section 2, we review the relevant theoretical and experimental literature. The theoretical model underlying our experiment is presented in Section 3. Section 4 describes the experimental design and procedures. Results are presented in Section 5, and Section 6 concludes.

2 Related literature

We start with a brief overview of the theoretical literature on contests with entry and information disclosure, and then summarize the relevant experimental studies. Contests with entry have been modeled in several ways that broadly fall into one of the following categories: (i) exogenous stochastic entry, where the number of entrants follows a given distribution (Münster, 2006; Myerson and Wärneryd, 2006; Lim and Matros, 2009; Fu, Jiao and Lu, 2011; Kahana and Klunover, 2015, 2016; Drugov and Ryvkin, 2017; Boosey, Brookins and Ryvkin, 2017*a*); (ii) endogenous entry into a single contest (Higgins, Shughart and Tollison, 1985; Gradstein, 1995; Fu and Lu, 2010; Kaplan and Sela, 2010; Fu, Jiao and Lu, 2015); and (iii) endogenous entry into one of several contests (Azmat and Möller, 2009; DiPalantino and Vojnovic, 2009; Konrad and Kovenock, 2012; Morgan, Sisak and Várdy, 2017; Azmat and Möller, 2018).[2]

The contest settings we consider in this paper fall into category (ii), augmented by a variation regarding the disclosure of the number of entrants.[3] For Tullock (1980) contests with exogenous stochastic entry and the number of entrants following a binomial distribution, Lim and Matros (2009) demonstrate that *ex ante* aggregate investment is independent of disclosure. The same result holds in the case of endogenous entry (Fu, Jiao and Lu, 2015). Fu, Jiao and Lu (2011) and Feng and Lu (2016) generalize the results of Lim and Matros (2009) to lottery contests with arbitrary impact functions and contest size distributions, and show that either full or no disclosure can be optimal depending on the properties of the impact function. For rank-order tournaments (Lazear and Rosen, 1981), Drugov and Ryvkin (2017) show that optimal disclosure depends on the curvature of the players' marginal cost of effort. For group contests with a stochastic number of players in each group, Boosey, Brookins and Ryvkin (2017*a*) show that aggregate investment (weakly) increases when the number of players in each group is disclosed.

[2] There is a parallel theoretical literature on auctions with entry that can be categorized similarly: (i) auctions with exogenous stochastic entry (e.g., McAfee and McMillan, 1987; Harstad, Kagel and Levin, 1990; Levin and Ozdenoren, 2004); (ii) endogenous entry into a single auction (e.g., Levin and Smith, 1994; Pevnitskaya, 2004); and (iii) endogenous entry into one of several competing auctions (e.g., Wolinsky, 1988; McAfee, 1993; Peters and Severinov, 1997). Experimental studies on auctions with entry include Dyer, Kagel and Levin (1989), Ivanova-Stenzel and Salmon (2004), Isaac, Pevnitskaya and Schnier (2012), Palfrey and Pevnitskaya (2008) and Aycinena and Rentschler (forthcoming).

[3] Many studies of disclosure focus on information about contestants' types (e.g., ability or valuation) (Hurley and Shogren, 1998*a*,*b*; Denter, Morgan and Sisak, 2014; Epstein and Mealem, 2013; Kovenock, Morath and Münster, 2015; Serena, 2015; Zhang and Zhou, 2016; Lu, Ma and Wang, 2017; Heijnen and Schoonbeek, 2017), but this dimension of information disclosure is irrelevant in our setting with symmetric players. There is also a growing theoretical literature on the effects of information disclosure across stages in dynamic contests (e.g., Aoyagi, 2010; Ederer, 2010; Rieck, 2010; Halac, Kartik and Liu, 2017; Klein and Schmutzler, 2017*b*), and some recent experimental tests of these predictions (e.g., Ludwig and Lünser, 2012; Deck and Kimbrough, 2017; Klein and Schmutzler, 2017*a*).

Within the vast experimental literature on contests (for a review, see Dechenaux, Kovenock and Sheremeta, 2015), we are only aware of three studies of contests with entry. Anderson and Stafford (2003) test the predictions of Gradstein (1995) by manipulating the degree of contestants' heterogeneity, total number of potential contestants, and size of the entry fee. The game proceeds in two stages. In the first stage, participants choose between entering the contest and paying an entry fee, or staying out at no cost. In the second stage, entry decisions are fully disclosed and participants simultaneously and privately compete in a Tullock contest. As predicted, entry is discouraged by higher entry fees. Also, consistent with most of the literature (Sheremeta, 2013), substantial overbidding is observed in all treatments. In the experiment of Morgan, Orzen and Sefton (2012), entry decisions are made sequentially in continuous time, and the number of prior entrants is publicly observable. The authors manipulate the size of the prize and find, consistent with theory, that entry and investment both increase in the prize. However, entry and investment levels are both above (resp. below) the theoretical predictions when the prize is low (resp. high). Finally, Boosey, Brookins and Ryvkin (2017*b*) test the predictions of Lim and Matros (2009) for contests with exogenous stochastic entry where the number of entrants follows a binomial distribution with parameters (n, q). Using a 2×2 design, they vary the maximum number of entrants, n, and entry probability, q, and find considerable support for the comparative statics as well as point predictions of the theory, with the exception of substantial overbidding in the treatment where both n and q are high.

As far as we know, the present paper is the first to study experimentally the effects of information disclosure in a contest with endogenous entry. A study conceptually closest to ours is by Aycinena and Rentschler (forthcoming) who study this type of information disclosure in first-price sealed-bid auctions and English ascending clock auctions. They find that concealing the number of entrants yields higher revenue in first-price auctions, but disclosing the number of entrants is optimal in English clock auctions. Both effects are due to differences in bidding and not in entry frequencies. Our results are somewhat similar, as we find entry frequencies affected by the entry fee but not so much by disclosure policy, and aggregate investment affected by disclosure in some, but not all cases.

3 The model and predictions

There are $n \geq 2$ identical risk-neutral players indexed by $i \in N = \{1, \ldots, n\}$. The game consists of two stages. In stage 1, the players simultaneously and independently decide whether or not to enter the contest. Players who choose to enter move on to stage 2, while all other players receive outside option payment $\omega \geq 0$. Let $M \subseteq N$ denote the subset of entrants. In stage 2, each entrant $i \in M$ simultaneously and independently chooses investment $x_i \geq 0$. The probability that entrant $i \in M$ wins prize $V > 0$ is given by the lottery contest success function of Tullock (1980),

$$P_i = \begin{cases} \frac{x_i}{\sum_{j \in M} x_j}, & \text{if } \max_{j \in M} x_j > 0 \\ \frac{1}{|M|}, & \text{otherwise} \end{cases} \quad (1)$$

In this paper, we focus on how the availability of information at the beginning of stage 2 affects entry and investment decisions. Specifically, we consider two information conditions – Disclosure and No Disclosure. Under Disclosure, the number of entrants is disclosed prior to the investment decisions in stage 2, whereas under No Disclosure the number of entrants is not disclosed.

The solution concept we use is subgame-perfect Nash equilibrium (SPNE). We also impose a symmetry assumption, i.e., we consider equilibria in which all (active) players use identical strategies at each stage.[4] Let $q \in [0, 1]$ denote a symmetric entry probability in stage 1. As shown by Lim and Matros (2009),[5] *ex ante*, the unique symmetric equilibrium investment in the second stage is independent of disclosure and given by the equation

$$x^*(q) = V \sum_{k=0}^{n-1} \binom{n-1}{k} q^k (1-q)^{n-1-k} \frac{k}{(1+k)^2}. \quad (2)$$

Here, the equilibrium investment is given by the weighted average of equilibrium investments in the lottery contest of $(k+1)$ players, $x^*_{k+1} = \frac{Vk}{(k+1)^2}$, with weights equal to the probabilities of different realizations of the number of other entrants, k, from an entrant's perspective. The *ex ante* equilibrium payoff of an entrant is, therefore, the weighted average of payoffs in the lottery contest of $(k+1)$ players, $\pi^*_{k+1} = \frac{V}{(k+1)^2}$:

$$\pi^*(q) = V \sum_{k=0}^{n-1} \binom{n-1}{k} q^k (1-q)^{n-1-k} \frac{1}{(k+1)^2}. \quad (3)$$

Under Disclosure, the symmetric mixed strategy SPNE with equilibrium entry probability $q^* \in (0, 1)$ is determined by the indifference condition $\pi^*(q^*) = \omega$. It can be shown that $\pi^*(q)$ is monotonically decreasing,[6] and hence a unique q^* exists provided $\pi^*(1) = \frac{V}{n^2} < \omega$

[4]In addition to symmetric mixed strategy equilibria we consider here, this game may have asymmetric equilibria in which some number of players enter for sure while others stay out. Our experimental data does not support any systematic asymmetric play.

[5]For more general results on disclosure, see also Fu, Jiao and Lu (2011).

[6]Following the standard argument for games with endogenous entry (Levin and Smith, 1994), $\pi^*_q = \frac{1}{q(1-q)} \mathrm{Cov}(\pi^*_{k+1}, k) < 0$ because π^*_{k+1} is decreasing in k.

and $\pi^*(0) = V > \omega$. Under No Disclosure, the existence of the symmetric equilibrium with the same entry probability and bidding is established in a more general setting by Fu, Jiao and Lu (2015).

Thus, the basic equilibrium analysis of our setting provides a prediction that disclosure has no effect on behavior. However, it is well-known that behavior in contest experiments can deviate substantially from the predictions of standard money-maximizing equilibrium models. One of the robust findings in the literature on contests with deterministic group size is overbidding relative to the risk-neutral Nash equilibrium (see, e.g., a survey by Sheremeta, 2013). At the same time, recent experimental results for contests with exogenous group size uncertainty (Boosey, Brookins and Ryvkin, 2017*b*) suggest that overbidding is substantially mitigated when the number of players is stochastic and undisclosed, and when there is a nontrivial probability for a player to be the only entrant. In our setting, the probability of entry is endogenous but can be manipulated via the outside option ω. In the experiment, we vary ω between a high value corresponding to a low probability of entry, and hence a high probability for an entrant to be alone, and a low value that leads to a relatively high entry probability. We expect disclosure to have different effects in these settings due to the differential effect of group size uncertainty on overbidding. Specifically, we expect disclosure to have no effect on aggregate investment behavior when ω is relatively low, but to lead to higher investment when ω is relatively high.

4 Experimental design

Each session of our experiment consisted of two parts. In Part 1, identical across all sessions, we measured subjects' attitudes towards risk, ambiguity, and losses. Each of these attitudes was elicited using a "list-style" environment similar to the methods used by Holt and Laury (2002) and Sutter et al. (2013).[7] Lists for the three measures were presented in a random order. One of the lists, and one of the rows in that list, were

[7] In each case, subjects were presented with a list of 20 choices between a sure amount of money and a gamble with two outcomes. The sure amounts of money changed gradually from the top to the bottom of the list. Subjects were asked to select a row where they were willing to switch from preferring a gamble to preferring a sure amount. In the risk list, the gamble was a lottery $(0, \$2; 0.5, 0.5)$ and sure amounts changed between \$0.10 and \$2; in the ambiguity list, the same sure amounts were used but the gamble was a lottery $(0, \$2; p, 1-p)$, with a uniform random p drawn from $[0, 1]$ and not disclosed to subjects; in the loss list, the gamble was a lottery $(0, -\$2; 0.5, 0.5)$ and sure amounts changed between $-\$2$ and $-\$0.10$. Our measures for risk aversion (RA) and loss aversion (LA) were constructed using the row numbers where subjects switched. The measure for ambiguity aversion (AA) was constructed as the difference between the row numbers where the subject switched in the ambiguous and risky lists.

selected randomly for actual payments.[8] Subjects were not informed about their payoffs from Part 1 until the very end of the experiment.

Part 2, the main portion of the experiment, consisted of a sequence of contest games with endogenous entry. We implemented a 2×2 between-subject design. In the first dimension, we varied whether or not the number of entrants was disclosed to subjects who entered the contest. In the second dimension, we varied the outside option, ω, paid to a subject who chose not to enter the contest, between a low value, $\omega = 6$, and a high value, $\omega = 48$. The resulting four treatments are referred to as D6, D48, ND6, and ND48, where D stands for Disclosure and ND for No Disclosure. Table 1 summarizes the parameters as well as the number of sessions, subjects and independent groups for each treatment.

For the main part of the experiment (Part 2), the subjects participated in 41 rounds of a two-stage contest game. Before the first round, they were randomly placed into groups consisting of six subjects each. These groups were fixed for the duration of the experiment, and interactions between subjects were confined to be within groups. At the beginning of each round, all subjects were given an endowment of 120 points.

In the first stage of the game, subjects were asked to choose whether to Enter the second stage contest, or Not Enter and receive the outside option payment, ω. Thus, subjects who chose Not Enter received $120 + \omega$ points for the round. Only subjects who chose Enter participated in the second stage. We refer to these subjects as *active subjects* or *active group members*. The number of active group members in a given round could be any integer from zero (0) to six (6).

In the second stage, active subjects (if present) were asked to choose how many points (out of their endowment) they wanted to invest into a project. In the Disclosure (D) treatments, subjects who chose Enter were shown the total number of active group members *before they made their investment decisions*. In contrast, in the No Disclosure (ND) treatments, subjects who chose Enter were required to make their investment decisions without knowing the number of active group members in Stage 2. Moreover, the number of active group members in the ND treatments was never revealed to the subjects, even after investment decisions were made.

An active subject's project could either succeed or fail, with success determined randomly according to the contest success function (1). If the project was successful (resp. failed) the subject received 120 (resp. 0) points in revenue for the round. Therefore, including their endowment for the round, a subject who invested x received $240 - x$ points

[8] If a subject's choice in that row were the sure amount of money, that amount was paid; if the choice were a lottery, the outcome was randomly realized.

Treatment	Disclosure	ω	Sessions	Subjects	Groups
D6	Y	6	2	36	6
D48	Y	48	2	36	6
ND6	N	6	2	36	6
ND48	N	48	2	36	6
Total			8	144	24

Table 1: Summary of experimental treatments.

for the round if her project was successful, or $120 - x$ points for the round if her project failed. After all investment decisions were made, active subjects were shown only their own investment, the outcome of their project, and their own payoff. In particular, regardless of the treatment, active subjects were not informed about the decisions or payoffs of any other active group members. Similarly, subjects who chose Not Enter in Stage 1 were only shown their own payoff at the end of the round.

At the beginning of round 41 (the last round), we also elicited subjects' beliefs. First, we asked them to guess the number of *other* subjects who will choose Enter in round 41. Second, we asked them to guess the average investment made by *other* subjects who choose Enter in round 41. Subjects were paid \$1 if their guess about the number of others who choose Enter was correct, and paid \$1 if their guess about the average investment of others who choose Enter was within 10 points of the actual average investment of others.[9] After these beliefs were elicited, subjects participated in the same two-stage game as in all previous 40 rounds. At the end of Part 2, the payoffs from five randomly selected rounds were counted towards final earnings, at the exchange rate of \$1 = 60 points. Total earnings were calculated by adding together Part 1 earnings, Part 2 earnings (including any payments from the belief elicitation), and the show-up fee.

We conducted a total of eight sessions (two sessions per treatment) in November 2017. A subject could only participate in one session, and therefore only in one treatment. All sessions were conducted using z-Tree (Fischbacher, 2007), with subjects making decisions at visually separated computer terminals at the XS/FS laboratory at Florida State University. A total of 144 subjects (68.75% of them female) were randomly recruited via ORSEE (Greiner, 2015) from a subpopulation of FSU students who pre-registered to receive announcements about participation in upcoming experiments. Instructions were distributed and read aloud prior to the start of each part. The instructions for Part 2 of

[9]We find that beliefs about investment are fairly accurate in all treatments; however, beliefs about entry are not, even in treatments with disclosure, where we expected average beliefs to be consistent with the feedback provided to entrants across the previous rounds. We provide summary statistics and a brief description of beliefs in the Appendix B, but do not use them in our analysis.

	Entry			Investment		
Treatment	Rd. 1-40	Rd. 26-40	Predicted	Rd. 1-40	Rd. 26-40	Predicted
D6	0.617	0.578	0.771	37.13	35.41	19.94
	(0.0421)	(0.0445)		(4.53)	(5.66)	
D48	0.396	0.339	0.232	46.18	45.96	20.50
	(0.0172)	(0.0245)		(6.18)	(6.78)	
ND6	0.546	0.506	0.771	43.42	45.15	19.94
	(0.0153)	(0.0218)		(3.22)	(4.45)	
ND48	0.413	0.370	0.232	33.89	28.32	20.50
	(0.0218)	(0.0270)		(3.14)	(3.36)	

Table 2: Average entry and average investment by treatment, with robust standard errors in parentheses, clustered by group.

the experiment are provided in Appendix C.[10] A session lasted approximately 80 minutes, with subjects earning \$19.96, on average, including a \$7.00 show-up fee.

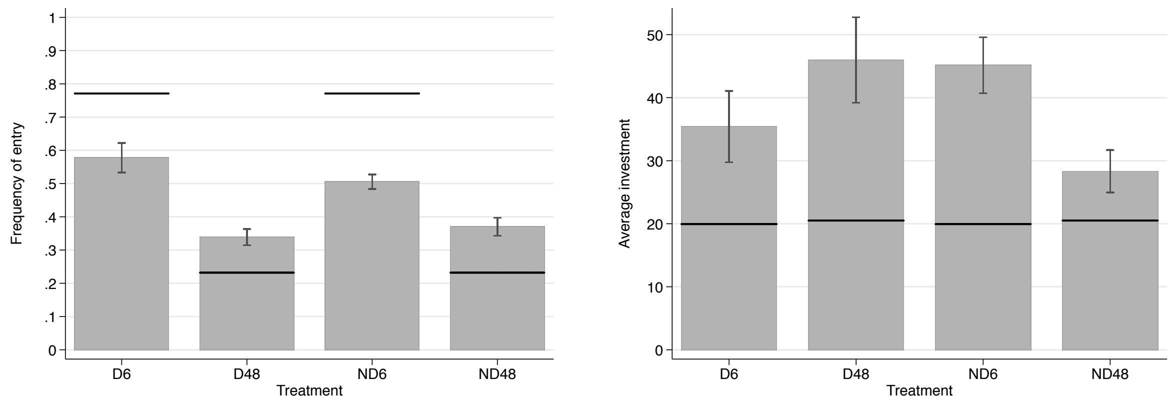
5 Results

5.1 Aggregate results

We begin by summarizing average entry and average investment for each treatment in Table 2. We compute the average entry and investment using all rounds (1 - 40) as well as using only the last 15 rounds (26 - 40).[11] We restrict attention to rounds 26 - 40 because we would like to focus on long-run, converged behavior of experienced subjects, and there is a significant time trend observed for entry decisions using all rounds (cf. Table 3), and even using the last 20 rounds, but the time trend is absent in the last 15 rounds. For the purposes of comparison, we also report the equilibrium prediction for each treatment. For entry, this is the equilibrium probability of entering the contest. For investment, we report the expected equilibrium investment for D6 and D48, given the equilibrium distribution of group sizes. As discussed in Section 3, these are equal to the equilibrium investment levels for the corresponding ND6 and ND48 treatments.

[10]Part 1 instructions are straightforward and available from the authors upon request.

[11]We exclude round 41 from the main analysis because subjects' beliefs about entry and investment of others were elicited at the beginning of that round, which could influence behavior.



(a) Frequency of entry

(b) Average investment

Figure 1: Frequency of entry and average investment by treatment, using rounds 26 - 40. Error bars represent the standard error of the mean, clustered by group. Solid reference lines indicate equilibrium point predictions.

Entry. Figure 1a shows the frequency of entry across treatments using data from rounds 26 - 40. Comparing the empirical entry frequencies to equilibrium point predictions (cf. also Table 2), we observe significant *under-entry* when ω is low (D6 and ND6), and significant *over-entry* when ω is high (D48 and ND48).[12] However, comparative statics across treatments are consistent with theory.

In order to measure the aggregate treatment effects, we estimate a Probit regression model for the entry decision, with treatment dummies and a time trend included as explanatory variables. The estimated marginal effects are reported in column (1) (using all rounds) and column (2) (using the last 15 rounds) of Table 3. As illustrated by Figure 1a, using the last 15 rounds, we find a significant negative effect on the probability of entry when ω increases from 6 to 48, for both the D and ND treatments.[13] Meanwhile, we find no significant differences between D6 and ND6 ($p = 0.122$), or between D48 and ND48 ($p = 0.354$).[14] We also note that, although there is a significant, negative time

[12] We use a Wald test comparing the estimated constant in a linear regression (with standard errors clustered at the group level) to the SPNE prediction. For all treatments, $p < 0.01$.

[13] $p < 0.001$ for both D6 vs. D48 and ND6 vs. ND48, using the Wald test comparing regression coefficients with standard errors clustered by group. Unless otherwise specified, all reported p-values correspond to Wald tests using the same level of clustering.

[14] Significance results are the same if we use all rounds, except that the entry frequency in ND6 is also (marginally) significantly lower than in D6, with $p = 0.093$. Moreover, these results are also supported by nonparametric Mann-Whitney-Wilcoxon (ranksum) tests. Using average entry at the group level as the unit of observation, we again find a significant negative effect of entry as ω goes from 6 to 48 for both D (Round 1 - 40 and Round 26 - 40: $p = 0.004$) and ND (Round 1 - 40: $p = 0.004$, Round 26 - 40: $p = 0.010$) treatments, and we find no effect of disclosure for either the $\omega = 6$ (Round 1 - 40: $p = 0.228$,

	Enter$_t$		Investment$_t$	
	(1) $1 \leq t \leq 40$	(2) $26 \leq t \leq 40$	(3) $1 \leq t \leq 40$	(4) $26 \leq t \leq 40$
ND6	-0.074*	-0.071	6.287	9.815
	(0.044)	(0.046)	(5.180)	(6.761)
D48	-0.220***	-0.231***	9.006	10.32
	(0.042)	(0.044)	(7.124)	(8.233)
ND48	-0.204***	-0.201***	-3.294	-7.123
	(0.044)	(0.046)	(5.129)	(6.155)
Period	-0.0043***	-0.00097	-0.0858	0.396
	(0.0007)	(0.0026)	(0.0821)	(0.323)
Constant			38.82***	22.39*
			(4.025)	(12.39)
N	5760	2160	2840	968

Table 3: Probit and OLS regression results. Columns (1) and (2) report marginal effects of a Probit regression model. Columns (3) and (4) report coefficient estimates for an OLS regression model. Standard errors in parentheses are clustered by group. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

trend when we use all rounds, Period has no effect when we use just the last 15 rounds.

Result 1 *(i) When ω is low (high), we observe significant under-entry (over-entry), relative to the SPNE prediction, regardless of the disclosure rule.*

(ii) Consistent with comparative static predictions, the frequency of entry is significantly lower when ω is high than when it is low, both with and without disclosure.

(iii) Disclosure has no significant effect on entry for either value of ω.

These findings are unchanged if we include controls for gender, or our elicited measures of risk aversion (RA), ambiguity aversion (AA), and loss aversion (LA). Furthermore, we find no significant differences in entry based on gender, AA, or LA, although subjects who are more risk averse are, on average, significantly less likely to enter ($p = 0.011$).[15] In Section 5.2, we explore the effects of risk aversion on entry in more detail and show that they are different across treatments.

Investment. We report the average investment levels for entrants in Table 2 and illustrate the treatment comparisons using rounds 26 - 40 in Figure 1b. In all four treatments,

Round 26 - 40: $p = 0.296$) or $\omega = 48$ (Round 1 - 40: $p = 0.873$, Round 26 - 40: $p = 0.470$) treatments.

[15]Regression results with these controls are not reported, but available upon request.

average investment is significantly higher than the SPNE prediction, whether we use all rounds or just the last 15 rounds.[16] For comparisons across treatments, columns (3) and (4) in Table 3 report the coefficient estimates for an OLS regression model with treatment dummies and a time trend. We find that average investment is significantly higher in ND6 than in ND48 ($p = 0.004$) and significantly higher in D48 than in ND48 ($p = 0.022$), over the last 15 rounds. However, none of the other pairwise comparisons indicate significant differences. In particular, when the number of entrants is disclosed, we observe higher average investment for $\omega = 48$ than for $\omega = 6$, but the difference is not statistically significant ($p = 0.223$). Similarly, average investment when $\omega = 6$ is qualitatively, but not significantly, higher without disclosure ($p = 0.160$).[17] We summarize our findings with respect to investment as follows.

Result 2 *(i) The average investment of entrants is significantly higher than the SPNE prediction in all treatments.*

(ii) An increase in ω leads to significantly lower average investment under No Disclosure, but has no effect when there is Disclosure.

(iii) Disclosure has a significant positive effect on average investment when ω is high, but no effect when ω is low.

The findings reported in Result 2 are all robust to the inclusion of individual controls for gender, RA, AA, and LA, and none of these controls have a significant effect on investment. Thus, while risk aversion tends to generate selection into the contest, it does not explain any of the variation in investment decisions by those who enter.

Total investment and revenue across treatments. Although the preceding analysis has focused on the average investment of entrants only, it can also be useful to compare average total investment, or total revenue, generated by different combinations of outside option and disclosure rule. This comparison may be of particular interest to contest designers who seek to maximize (or minimize) expected total investment when faced with a pool of potential entrants.

Figure 2 shows the average total investment over the last 15 rounds for each treatment. Specifically, we calculate the average investment *without* excluding those individuals who

[16] Wald tests; $p = 0.041$ for D6, $p = 0.013$ for D48, $p = 0.002$ for ND6, and $p = 0.067$ for ND48.

[17] Results regarding investment levels do not change when considering all rounds, but p-values for ND6 vs. ND48 ($p = 0.032$) and D48 vs. ND48 ($p = 0.070$) comparisons increase. Treatment comparisons are also similar when conducting nonparametric Wilcoxon-Mann-Whitney (rank-sum) tests, as average investment in ND6 and D48 are both significantly higher than in ND48 ($p = 0.010$ and $p = 0.055$, respectively) for the last 15 rounds. When considering all rounds, only the ND6 vs. ND48 comparison remains significant ($p = 0.078$); p-value for D48 vs. ND48 is $p = 0.200$.

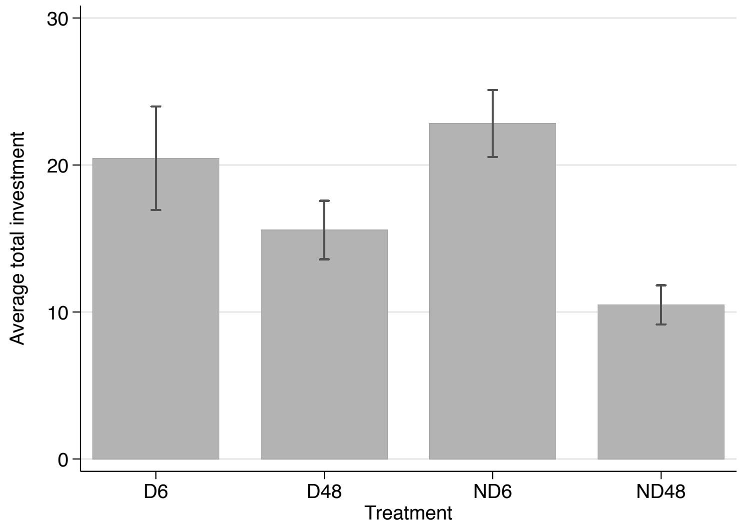


Figure 2: Average total investment by treatment, using rounds 26-40. Error bars represent the standard error of the mean, clustered by group.

chose not to enter the contest. Instead, those subjects are treated as having invested nothing. We also regress investment on treatment dummies and a time trend, in order to test for differences across treatments. Consistent with Figure 2, average total investment is significantly lower in ND48 than in ND6 ($p < 0.001$) and significantly lower in ND48 than in D48 ($p = 0.032$). Although it is somewhat lower in D48 than in D6, the difference is not significant ($p = 0.209$). Likewise, we find no significant difference between D6 and ND6 ($p = 0.552$). Thus, treatment effects for average total investment are the same as for investment *conditional on entry* reported in Result 2. Specifically, an increase in the outside option only significantly reduces average *total* investment under No Disclosure. Similarly, disclosure only significantly increases average total investment when the outside option is high.

Overall, Figure 2 suggests that, if the contest designer has the ability to set both an entry fee and the disclosure rule, total investment is higher with a low entry fee, and insensitive to the disclosure rule. Thus, even in settings where the contest designer is unable to observe the number of entrants (making disclosure impossible), she should set a lower entry fee in order to increase expected revenue. Conversely, in cases where the contest designer has limited control over the size of the participants' outside option, and the outside option is high, committing to disclose the number of entrants raises the average total investment.

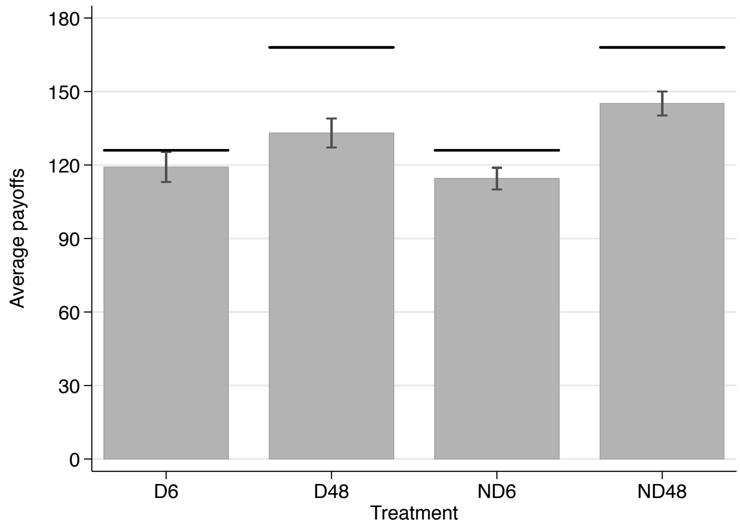


Figure 3: Average payoffs for entrants, by treatment, using rounds 26 - 40. Solid reference lines indicate the (fixed) payoff for non-entrants. Error bars represent the standard error of the mean, clustered by group.

Payoffs. Finally, we also consider the comparison between payoffs for entrants and non-entrants in each treatment. In equilibrium, payoffs are equalized. However, given that both the observed entry frequencies and average investment levels are different from the SPNE, it seems more plausible that entrants are earning lower payoffs (on average) than non-entrants, especially when $\omega = 48$. Figure 3 compares the average payoff of entrants to the fixed payoff from not entering, for each treatment.[18]

When the outside option is low (D6 and ND6), the average payoff of entrants is only slightly lower than the payoff of a non-entrant. While this is somewhat consistent with the equilibrium condition that payoffs are equalized, it reflects the opposing influences of under-entry (relative to SPNE) and overbidding on entrants' payoffs. In contrast, when the outside option is high (D48 and ND48), we observe both over-entry and overbidding, such that entrants earn, on average, significantly less than the payoff of a non-entrant. In this case, the dual departures from equilibrium in entry and investment decisions reinforce one another to lower average payoffs of entrants.

5.2 Risk aversion and entry

Over the next few sections, we explore entry and investment decisions in greater detail. First, we examine the more nuanced effects of risk aversion on entry in the different

[18]Note that both payoff calculations include the endowment (120 points) given to players in each round.

	$\omega = 6$	$\omega = 48$
Enter$_t$	(1)	(2)
NDω	0.201*	0.053
	(0.097)	(0.172)
RA	-0.007	-0.017***
	(0.007)	(0.005)
RA$\times$NDω	-0.034***	-0.001
	(0.011)	(0.018)
Period	-0.006	0.004
	(0.003)	(0.003)
Constant	0.834***	0.379***
	(0.161)	(0.112)
N	1080	1080

Table 4: Linear probability model regression results of entry on risk aversion. Column (1) compares D6 and ND6 (with D6 the omitted dummy), while Column (2) compares D48 and ND48 (with D48 the omitted dummy). Standard errors in parentheses are clustered by group. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

treatments. In order to do so, we compare treatments in pairs. Table 4 reports the coefficient estimates for the linear probability model restricted to the two most relevant pairs of treatments. In each case, we include as regressors a treatment dummy for No Disclosure (NDω), the elicited risk-aversion measure (RA), the interaction of the two, and a time trend. Column (1) compares D6 and ND6. In this case, we observe no effect of risk aversion in D6, but a significantly negative effect of risk aversion on entry in ND6. Thus, when the outside option is low ($\omega = 6$), risk aversion is only a factor when the number of entrants is not disclosed. In contrast, as shown in Column (2), we find that when the outside option is high ($\omega = 48$), risk aversion significantly reduces entry in both D48 and ND48, but the effects are not sensitive to disclosure.

Result 3 *(i) When $\omega = 6$, more risk averse individuals are less likely to enter, but only when the number of entrants is not disclosed.*

(ii) When $\omega = 48$, more risk averse individuals are less likely to enter regardless of the disclosure rule. Furthermore, the magnitude of the effect is not sensitive to disclosure.

These findings show that risk aversion affects entry in different ways, depending on the outside option. We argue that the following intuition provides a straightforward explanation. When entry requires giving up only a small payment, as is the case when

$\omega = 6$, the strategic uncertainty introduced when group size is not disclosed is a more prominent source of risk than the uncertainty about whether or not the entrant may win (enough to justify entry). In contrast, when entry requires the subject to give up a large outside option payment, as when $\omega = 48$, the risk of not winning the contest (and thereby recovering at least the forgone outside option) dominates the additional strategic uncertainty related to the disclosure of group size.

5.3 Explaining behavior using QRE

In this section, we address the differences between observed and predicted levels of entry and investment across treatments. In particular, note that a subject making completely random entry decisions would enter the contest with probability 0.5 regardless of parameters. While the SPNE entry frequency is relatively high (0.771) for $\omega = 6$ and low (0.232) for $\omega = 48$, the observed frequencies (0.578 and 0.339, respectively) are shifted towards 0.5 in each case. Such deviations are consistent with boundedly rational subjects making random errors when choosing an optimal strategy. We explore this explanation in more detail by deriving Quantal Response Equilibrium (QRE) predictions for our two-stage games.

We compute the symmetric subgame-perfect logit QRE for the two-stage contest under each information condition for a given ω. In a normal-form QRE, players choose each available strategy $s \in S$ with some probability $p(s)$ that is increasing in the expected payoff $\pi(s)$ of using that strategy averaged over the behavior of all other players. In the logit QRE, this probability takes the form

$$p(s) = \frac{\exp[\lambda \pi(s)]}{\sum_{s' \in S} \exp[\lambda \pi(s')]} \tag{4}$$

where $\lambda \in [0, \infty)$ represents the inverse of the level of "noise," or errors in players' decision making. As $\lambda \to 0$, behavior becomes completely random, with $p(s) \to \frac{1}{|S|}$, whereas in the opposite limit, $\lambda \to \infty$, QRE converges to the Nash equilibrium of the original game.

QRE predictions have successfully rationalized off-equilibrium investment behavior (e.g., overbidding and overspreading) for a variety of one-stage auction and contest experiments (see, e.g., Goeree, Holt and Palfrey, 2002; Sheremeta, 2010; Lim, Matros and Turocy, 2014; Brookins and Ryvkin, 2014). Morgan, Orzen and Sefton (2012) derive the symmetric subgame-perfect QRE entry probabilities for their two-stage endogenous entry contest game. However, they do not compute the full two-stage equilibrium; instead, for expected second-stage payoffs they use the empirical average payoffs conditional on the number of entrants. In contrast, we assume that players are boundedly rational at *both*

	Entry			Investment		
Treatment	Predicted	Observed	QRE	Predicted	Observed	QRE
D6	0.771	0.578	0.548	19.94	35.41	28.46
D48	0.232	0.339	0.343	20.50	45.96	50.07
ND6	0.771	0.506	0.550	19.94	45.15	28.32
ND48	0.232	0.370	0.343	20.50	28.32	50.12

Table 5: Entry and investment SPNE predictions, observed averages for rounds 26 - 40, and QRE predictions for $\hat{\lambda} = 0.7$, by treatment.

stages of the game, and hence, obtain QRE predictions for both entry and subsequent investment behavior.

We relegate the full technical details of our approach to Appendix A. However, two key features are worth emphasizing. First, for the Disclosure setting we use a full two-stage formulation of QRE,[19] where in stage 2 the entrants' strategy spaces are available investment levels, and at stage 1 it is the binary entry decision. For each realized number of entrants, we compute QRE probabilities for investments in stage 2; then, using those probabilities and resulting stage 2 payoffs, we calculate QRE entry probability in stage 1. In the No Disclosure setting, the two stages are effectively collapsed into one because the distribution of investment is independent of the number of entrants.

Second, since our objective is to explain both entry and investment behavior across all four treatments, we search for a value of the noise parameter λ that provides the best fit for the resulting eight averages (cf. Table 2). This task is complicated by the fact that, for any λ, the equilibrium payoffs scale with ω, such that the sensitivity to λ varies substantially with the size of the outside option. For our set of treatments, the values of ω are very different, making it impossible to find a single value of λ that reasonably fits all of the data. Our solution is to renormalize payoffs by ω, in a way that keeps the sensitivity to the noise parameter constant across treatments, and define $\hat{\lambda} = \lambda\omega$ as the single noise parameter to be fitted across treatments with different values of ω. Using the renormalized model, we select the noise parameter that minimizes a sum of squared errors (*SSE*) criterion evaluated over the eight data points. The best fit is provided by a value of $\hat{\lambda} = 0.7$.

[19]For a similar approach, see Ryvkin and Semykina (2017) who use QRE to explain behavior in a two-stage game where at the first stage players vote on a redistributive tax and at the second stage play a modified linear public good game with the median tax rate implemented.

Table 5 reports, for each treatment, the predicted entry and investment according to QRE with $\hat{\lambda} = 0.7$, alongside the SPNE prediction and the observed average entry and investment in rounds 26 - 40. As seen from the table, QRE fits the data well for entry frequency in all treatments. In particular, the QRE entry probabilities match the observations that subjects over-enter when $\omega = 48$, but under-enter when $\omega = 6$. However, Table 5 also shows that QRE cannot explain the patterns of investment. While QRE does capture the overbidding observed in all treatments, it does not explain why we observe higher investment levels in ND6 compared to ND48, which contradicts the SPNE comparative static. Instead, as we argue in the next section, these differences appear to be more consistent with the differential impacts of group size uncertainty on overbidding when the possibility of being the only entrant is non-negligible vs. negligible.

5.4 Investment and the number of entrants

In this section, we explore the relationship between investment and the number of entrants in the contest. In the disclosure treatments (D6 and D48), subjects can condition their investment decisions on the number of entrants. Thus, we expect variation in the average investment across different group sizes, in accordance with the comparative statics implied by the subgame equilibrium predictions in contests with different, known group sizes. In contrast, in the treatments without disclosure (ND6 and ND48), subjects cannot condition their investment on the number of entrants, and thus, average investment should be level across different realized (but undisclosed) group sizes.

Figure 4 shows the average investment, broken down by the number of entrants in the contest, for each of the four treatments. First, we examine the ND treatments, shown in the bottom two panels of Figure 4. As expected, average investment is not sensitive to the realized number of entrants in ND6 and ND48 ($p = 0.634$ and $p = 0.317$ for the slope, respectively). However, average investment in ND48 (for all numbers of entrants) is lower than in ND6. This difference is consistent with our motivation for studying the effects of the group size uncertainty induced by endogenous entry. In ND6, there is a negligible chance (in equilibrium) that an entrant is alone in the contest. As such, consistent with previous findings, we observe overbidding levels comparable to those observed in contests with known group size. In contrast, in ND48, the equilibrium entry probability induces group size uncertainty with a non-trivial chance of being alone in the contest. Again, consistent with previous findings, this leads to substantially less overbidding, on average, relative to the equilibrium prediction.

Next, we consider the D treatments, shown in the top two panels of Figure 4. As predicted, average investment in D6 and D48 indeed varies systematically with the realized

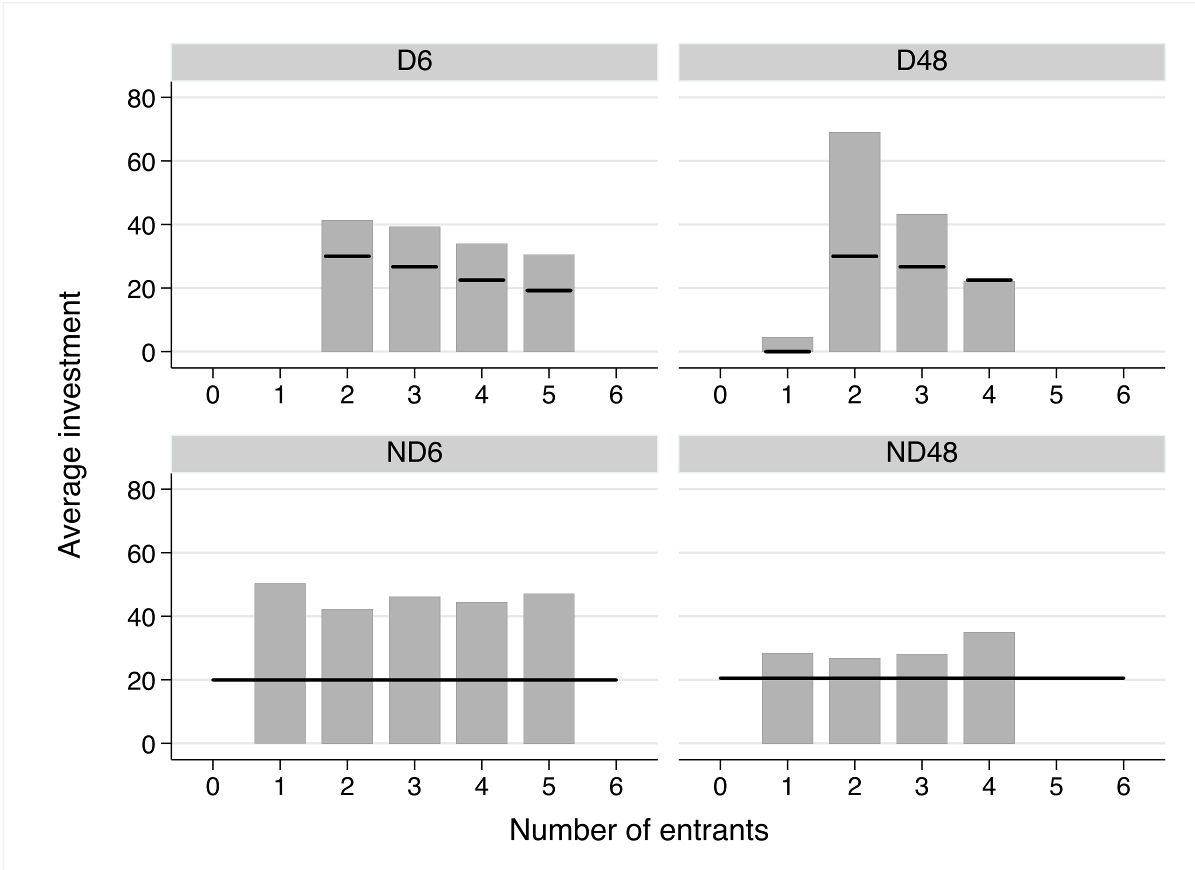


Figure 4: Average investment by number of entrants for each treatment (last 15 rounds). Solid reference lines indicate equilibrium point predictions.

number of entrants. First, consistent with their dominant strategy, individuals who learn that they are the only entrant in their group almost always choose zero investment.[20] Second, when there are at least two entrants, average investment is decreasing in the number of entrants k, consistent with the equilibrium predictions for contests with different group sizes. However, the patterns of the decline in D6 and D48 are quite different. In D6, the dependence of investment on k is rather weak ($p = 0.464$ for the slope in a regression of investment on the number of entrants),[21] and significant overbidding is observed for all $k \geq 2$. In contrast, in D48 the decline in average investment with respect to the number of entrants is strong and significant ($p = 0.027$ for the slope in a regression of investment

[20]In D48, there were 27 instances where only one player entered, and the entrant invested zero in 26 of those instances. In D6, due to the higher frequency of entry, there are no observations where only one player entered.

[21]However, average investment can be fitted fairly well with function $x_k^* = \frac{V(k-1)}{k^2}$, cf. Section 3. An OLS regression of individual investment on x_k^* without intercept produces slope estimate 1.47 ($p = 0.001$), indicating overbidding by about 50%, on average.

on k), and overbidding is decreasing in k.

What could be causing this variation in sensitivity to the number of entrants in the disclosure treatments? In D6, entry is relatively high and there are no contests with fewer than two entrants in the last 15 rounds. Furthermore, for each realized group size k, average investment levels in these contests are in line with the levels observed in the same size contests without entry. Consistent with the meta-analysis of Sheremeta (2013), average investment is above equilibrium for each group size, with increasing overbidding rates.[22] Thus, in D6 our entrants' behavior conditional on group size is consistent with the experimental contest literature.

In contrast, in D48, the forgone outside option, $\omega = 48$, appears to loom large over entrants' investment decisions in the contest. One possible explanation is that subjects who forgo a large outside option in order to enter the contest are more strongly motivated by a desire to win, as a means of justifying their entry decision. On the one hand, this would imply that subjects compete aggressively when there are just two entrants, which explains the spike in average investment at $k = 2$ for D48.[23] On the other hand, when the realized number of entrants is higher ($k = 3$ or 4), the effect of a strong desire to win is countered by the lower likelihood of winning. Looking at overbidding rates in D48, average investment is about 130% above equilibrium for $k = 2$, as opposed to 61.5% for $k = 3$. Most notably, average investment when $k = 4$ (22.00) is nearly identical to the equilibrium level (22.50). The decline in overbidding rate with group size, to the point of virtually zero overbidding for $k = 4$, is in stark contrast with the experimental literature on contests without entry.

Subjects who enter the contest in D48 likely do so with the hope that realized group size will be small ($k = 1$ or 2). Then, if the subject is alone, she can secure a much higher payoff than the outside option, while if there is only one other entrant, she may still fancy her chances of winning the contest by investing a high amount. However, if the realized group size is larger, the lower perceived likelihood of winning (and thus of securing a payoff that justifies entry) tends to mitigate overbidding.

[22] Average investment is 37.4% higher than equilibrium for $k = 2$, 47.1% higher for $k = 3$, 50.8% higher for $k = 4$, and 58.7% higher for $k = 5$.

[23] It is interesting to note that average investment is almost 70, which, even if an entrant wins with probability one, generates a maximum expected payoff of 50. If the probability of winning is 0.5, then the expected payoff from investing 70 is negative.

6 Conclusions

In contests where participants do not immediately observe the number of entrants, a disclosure policy can be a powerful tool in the organizer's hands. Given the co-existence of different modes of disclosure in the field, it is important, both from a positive and normative perspective, to understand the effects of disclosure on contest outcomes – entry and investment.

Our results inform on possible consequences of disclosing the number of players, which is the only form of interim disclosure available in a symmetric setting.[24] We find that disclosure has no effect on aggregate contest investment when the expected number of participants is relatively high, but a strong positive effect when the expected number of entrants is low.

The policy implications of our results are straightforward and appealing. For a principal willing to maximize contest investment, which may be beneficial in cases such as R&D or productive competition in organizations, it makes sense to commit to disclosing the number of entrants even when there is a risk of having only one entrant. In contrast, when contest investment can be viewed as counterproductive, such as in the case of lobbying or socially wasteful rent-seeking, the regulator may want to restrict information. Nevertheless, as the size of potential competition grows, the effects of disclosure are diminished.

Given that our results are driven by differential out-of-equilibrium overbidding, a key question for external validity is to what extent excessive spending is a feature of contests in the field, as opposed to just a laboratory phenomenon. While direct evidence is difficult to come by, there is plenty of indirect evidence that people spend too much on competition in various domains. Possibly the most well-studied settings are excessive entry and investment by entrepreneurs (Dunne, Roberts and Samuelson, 1989; Shane and Venkataraman, 2000) and by investors in the financial sector (Malmendier and Tate, 2005). Other examples, backed mostly by anecdotal evidence at this point, are the so-called law school bubble[25] and the prevalence of unrealistic expectations regarding career success in athletics or the arts.[26] Given how wide-spread, and well-documented, overbidding

[24] In settings with heterogeneous players, not just the number but also the abilities (or identities) of competitors may be disclosed or concealed. Such settings, with more complex, multi-dimensional disclosure policies are an interesting extension for future research.

[25] See, e.g., The New York Times article https://www.nytimes.com/2016/06/19/business/dealbook/an-expensive-law-degree-and-no-place-to-use-it.html

[26] For example, 26% of NCAA Division I male college athletes reported that their family expected them to have a professional career in sports or compete in the Olympics, while in reality the rate is about 3%, see http://usatodayhss.com/2017/do-parents-place-unrealistic-expectations-on-their-athletes.

is in laboratory contests, and our results on the moderating effects of uncertainty on overbidding, a more systematic exploration of these phenomena in the field is highly pertinent.

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A Details of our QRE approach

Let B denote the discretized set of available investments for entrants at the second stage.

No disclosure. Without disclosure, entrants must choose their investments without knowing the number of other entrants. Let Q_{nd} denote the symmetric QRE entry probability and $p_{nd}(b)$ denote the symmetric QRE probability of investing $b \in B$ for entrants. Then the expected payoff from investing b by an entrant is

$$\pi_{nd}(b) = V \sum_{k=0}^{n-1} \binom{n-1}{k} Q_{nd}^k (1 - Q_{nd})^{n-1-k} \sum_{b_1,\ldots,b_k \in B^k} p_{nd}(b_1) \ldots p_{nd}(b_k) \frac{b}{b + \sum_{l=1}^k b_l} - b. \tag{A.1}$$

The unconditional expected payoff of an entrant is $\pi_{nd} = \sum_{b \in B} p_{nd}(b)\pi_{nd}(b)$. Here,

$$p_{nd}(b) = \frac{\exp[\lambda \pi_{nd}(b)]}{\sum_{b' \in B} \exp[\lambda \pi_{nd}(b')]}, \quad Q_{nd} = \frac{\exp(\lambda \pi_{nd})}{\exp(\lambda \pi_{nd}) + \exp(\lambda \omega)}. \tag{A.2}$$

Disclosure. In this case, entrants observe the number of other entrants before they decide on investments. Let Q_d denote the symmetric QRE entry probability and $p_d(b;k)$ denote the symmetric QRE probability of investing b given the number of other entrants $k \in \{0, \ldots, n-1\}$. The expected payoff of an entrant observing k and investing b is

$$\pi_d(b;k) = V \sum_{b_1,\ldots,b_k \in B^k} p_d(b_1;k) \ldots p_d(b_k;k) \frac{b}{b + \sum_{l=1}^k b_l} - b, \tag{A.3}$$

where

$$p_d(b;k) = \frac{\exp[\lambda \pi_d(b;k)]}{\sum_{b' \in B} \exp[\lambda \pi_d(b';k)]}. \tag{A.4}$$

The unconditional payoff of an entrant (before k is observed) is

$$\pi_d = \sum_{k=0}^{n-1} \binom{n-1}{k} Q_d^k (1 - Q_d)^{n-1-k} \sum_{b \in B} p_d(b;k)\pi_d(b;k), \tag{A.5}$$

and the entry probability is

$$Q_d = \frac{\exp(\lambda \pi_d)}{\exp(\lambda \pi_d) + \exp(\lambda \omega)}. \tag{A.6}$$

Renormalization. For parameters corresponding to an interior mixed strategy NE at the entry stage, the unconditional payoffs π_{nd} and π_d defined above approach the NE value of ω as $\lambda \to \infty$. For a finite λ, the payoffs also scale with ω. Therefore, for values of ω varying substantially across treatments, it is impossible to find a single value of λ fitting all the data. Indeed, suppose some value of λ fits the empirical entry probability Q_{nd} for $\omega = 6$. That same λ cannot possibly fit Q_{nd} for $\omega = 48$ because both π_{nd} and ω are much larger in that treatment and hence the QRE entry probability has a much higher sensitivity to λ. We, therefore, argue that in order to fit the data from all treatments with a single QRE parameter, payoffs need to be renormalized to keep the sensitivity constant across treatments.

Define renormalized payoffs as $\hat{\pi}_{nd}(b) = \frac{\pi_{nd}(b)}{\omega}$, and similarly for all other payoffs in this section. Further, define the renormalized QRE parameter $\hat{\lambda} = \lambda\omega$. With such renormalization, the equations for the equilibrium distributions of investments do not change except hats are added to all payoffs and λ. The equations for the equilibrium entry probabilities become

$$Q_{nd} = \frac{\exp(\hat{\lambda}\hat{\pi}_{nd})}{\exp(\hat{\lambda}\hat{\pi}_{nd}) + \exp(\hat{\lambda})}, \quad Q_d = \frac{\exp(\hat{\lambda}\hat{\pi}_d)}{\exp(\hat{\lambda}\hat{\pi}_d) + \exp(\hat{\lambda})}. \tag{A.7}$$

Within any given treatment (or a set of treatments) with the same ω, the renormalized model is not distinguishable from the original QRE model except λ is rescaled. The goal of the renormalization is to be able to fit data from treatments with different values of ω with a single parameter $\hat{\lambda}$. A behavioral interpretation of this renormalization is consistent with the well-documented heuristic of *relative*, as opposed to absolute, concerns about changes in costs and prices (see, e.g., Garland and Newport, 1991; Krishna et al., 2002). In our setting, this corresponds to the assumption that subjects view the outside option ω as a reference payoff and interpret changes in their payoffs from entry as a proportion of ω.

Numerical method. For each calculation, we use renormalized payoffs defined above, a normalized prize value of $V = 1$, and discretized investment space $B = \{0.00, 0.05, \ldots, 1.00\}$. For no disclosure, the QRE is the set of entry and investment densities,

$$\{Q_{nd}\} \bigcup \{p_{nd}(0.00), p_{nd}(0.05), \ldots, p_{nd}(1.00)\},$$

which we obtain by iteratively and simultaneously solving the system of equations (A.2) until convergence.[27] QRE for disclosure is obtained similarly, i.e., iteratively and simultaneously solving equations (A.4), for $k = 1, \ldots, n-1$, and (A.6), and are given by entry

[27]Fixed-point algorithms are programmed in C++ and are available from the authors upon request.

and investment densities set

$$\{Q_d\} \bigcup \times_{k=1}^{n-1} \{p_d(0.00;k), p_d(0.05;k), \ldots, p_d(1.00;k)\}.$$

For a given outside option ω, let

$$b_{nd}^{QRE}(\omega) = \sum_{b' \in B} b' p_{nd}(b'), \quad b_d^{QRE} = \sum_{k=1}^{n-1} (Q_d^{QRE})^k (1 - Q_d^{QRE})^{n-1-k} \sum_{b' \in B} b' p_d(b';k)$$

denote average QRE investments and $Q_{nd}^{QRE}(\omega)$ and $Q_d^{QRE}(\omega)$ the associated QRE entry probabilities. Under our renormalization, we seek to find the $\hat{\lambda}$ that best fits observed entry and investment behavior. We therefore compute the QRE over a grid of $\hat{\lambda}$ points and select the value which minimizes the sum of squared errors (SSE) given by

$$\begin{aligned} SSE &= \textstyle\sum_{\omega \in \{6,48\}} \left[\left[Q_{nd}(\omega) - Q_{nd}^{QRE}(\omega) \right]^2 + \left[Q_d(\omega) - Q_d^{QRE}(\omega) \right]^2 \right. \\ &\quad \left. + \left[b_{nd}(\omega) - b_{nd}^{QRE}(\omega) \right]^2 + \left[b_d(\omega) - b_d^{QRE}(\omega) \right]^2 \right]. \end{aligned} \tag{A.8}$$

B Beliefs

In Table B.1, we report the average beliefs regarding entry and investment, elicited at the beginning of round 41. First, consider beliefs regarding entry. Formally, we elicited subjects' beliefs about the number of *other* entrants in round 41, i.e., not including themselves if they planned to enter. For the purpose of comparison, we also report the average observed number of other entrants using rounds 26-40, and the predicted number of other entrants using the equilibrium probability of entry. While both the predicted and observed levels are lower when $\omega = 48$, we observe no significant differences between beliefs about entry of others across the four treatments. While average beliefs are between the observed and predicted levels for D6 and ND6, they are far above the observed level (and even further above the predicted level) in D48 and ND48. Furthermore, even in the treatments with disclosure, where we expected the feedback received by entrants to guide beliefs towards the empirical average, subjects' beliefs are not particularly accurate.

Second, consider beliefs regarding investment. In this case, we elicited subjects' beliefs about the average investment of *other* entrants in round 41. Again, we report the average investment of other entrants computed using rounds 26-40, and the predicted average investment for each treatment. Overall, beliefs regarding others' investment are fairly accurate, although beliefs are above the empirical averages in all except the ND6 treatment. In some respects, this may be driven by subjects using their own average investment as the response to the belief elicitation (attributing their own behavior to others). Overall, we concluded that beliefs exhibited limited consistency and provided no additional explanatory power for our analysis.

	Entry			Investment		
	Beliefs	Observed	Predicted	Beliefs	Observed	Predicted
D6	3.50	2.89	3.86	40.69	36.53	19.94
	(0.401)	(0.223)		(2.199)	(4.453)	
D48	3.11	1.69	1.16	50.19	40.93	20.50
	(0.186)	(0.122)		(4.270)	(6.160)	
ND6	3.11	2.53	3.86	40.47	44.71	19.94
	(0.253)	(0.109)		(7.030)	(4.633)	
ND48	2.92	1.85	1.16	33.83	26.59	20.50
	(0.037)	(0.135)		(3.653)	(2.466)	

Table B.1: Average beliefs by treatment, compared with observed averages (rounds 26-40) and predicted levels for entry and investment. Standard errors reported in parentheses are clustered at the group level.

C Experimental instructions

We reproduce instructions for treatment D6 below. Footnotes, which were not part of the original instructions, highlight differences between D and ND treatments.

Instructions

All amounts in this part of the experiment are expressed in points. The exchange rate is 60 points = $1.

This part of the experiment consists of a sequence of 41 decision rounds.

Groups and matching

At the beginning of round 1, you will be randomly assigned to a group consisting of 6 participants, including you. You will remain in this group for the duration of this part of the experiment. That is, you will interact with the same 5 other participants in all 41 rounds.

Endowment

In each round, you will be given an endowment of 120 points. You may use any number of these points to make decisions in a given round.

Structure of a round

Each round consists of two stages: Stage 1 and Stage 2.

<u>Stage 1</u>

In this stage, you will need to decide whether you want to

- **ENTER Stage 2**, or
- **NOT ENTER Stage 2 and collect a fixed payment of 6 points.**

If you choose NOT ENTER, you will not proceed to Stage 2 and your payoff for the round will be the sum of your endowment (120 points) and the fixed payment (6 points), which is equal to 126 points.

If you choose ENTER, you will proceed to Stage 2.

Stage 2

Active group members

The total number of active members from your group in this stage will depend on the choices made by all members of your group in Stage 1. Only those group members who chose ENTER will be active in Stage 2; all others will be inactive. Thus, the total number of active group members, including you, can be 0, 1, 2, 3, 4, 5 or 6. Only active group members will make a decision in this stage. If you are active in Stage 2, the total number of active group members in the round (including you) will be shown at the top of the decision screen.[28]

Investment decisions

In this stage, if you are an active group member, you can invest any integer number of points from 0 to 120 into a project. The project can either succeed or fail. If your project succeeds, you will receive 120 points of revenue for the round. If your project fails, you will not receive any revenue for the round.

What is the likelihood that your project succeeds?

After you have made your investment decision, the outcome of your project will be determined. Only one of the active group members in your group can have a successful project. The **probability that your project succeeds** is given by:

$$\frac{\text{Number of points you invested in your project}}{\text{Sum of the points invested in projects by all active members of your group}}$$

For example, suppose you and one other member from your group are active. If you invested 10 points and the other active member invested 20 points, then the probability that your project succeeds is

$$\frac{10}{10+20} = \frac{10}{30} = \frac{1}{3} = 33.33\%.$$

For another example, suppose you and two other members from your group are active. If you invested 10 points and the other members invested 5 points and 25 points, then the probability that your project succeeds is

$$\frac{10}{10+5+25} = \frac{10}{40} = \frac{1}{4} = 25.00\%.$$

[28] An additional sentence was added to this paragraph in ND6: "However, the number of active group members will not be revealed to you at any point during or after the stage."

Lastly, if you are the only active group member in your group, then your project **always** succeeds (the probability is 100%), regardless of how much you invested.

Payoff calculation if you are ACTIVE in Stage 2
After determining the probability that your project succeeds, the software program will randomly determine whether your project succeeds or not, according to the calculated probability.

Then, if you are an active group member, your **individual payoff** for the round is determined as follows:

If your project succeeds:	If your project fails:
+120 (endowment)	+120 (endowment)
+120 (revenue)	+0 (no revenue)
− (points you invested)	− (points you invested)
240 − **(points you invested)**	120 − **(points you invested)**

Payoff calculation if you are NOT ACTIVE in Stage 2
If you are not active in Stage 2, your **individual payoff** for the round is determined as follows:

+120 (endowment)
+ (fixed payment of 6 points)
126

Feedback at the end of each round

At the end of each round, you will be informed about the decision you made in Stage 1 (ENTER or NOT ENTER), and your investment and project outcome if you were active in Stage 2. You will also be informed about your individual payoff for the round.

How are your earnings from this part determined?

You will participate in a series of 41 decision rounds. At the end of the series, **five** of these rounds will be chosen randomly (with all rounds being equally likely to be chosen). At the end of the experiment, you will be informed about which five rounds were chosen and your payoff from each of those five rounds. Then your earnings from this part will be the sum of your payoffs from the five randomly selected rounds.

Practice module

Before the actual decision rounds begin, you will participate in an unpaid practice module designed to help you better understand the Stage 2 environment. The module consists of three practice Stage 2 investment decisions. In this module, you will not interact with anyone else, and no decisions you make will be shown to anyone else. You will not earn anything from this practice module – it is only intended to help you better understand the rules of this part of the experiment.

In each Stage 2 practice decision, it is assumed that you chose ENTER at Stage 1, and therefore, you will be active in Stage 2. As in the actual decision rounds, you can choose how many points to invest into your project. In addition, **for these practice decisions only**, you can choose the project investments for the other active members of your group. In the actual decision rounds, the project investments for the other active members of your group will be the investments that were actually chosen by the other participants.[29]

Also for these practice decisions only, the computer will calculate the probability that your project succeeds for each of the three practice Stage 2 decisions. This allows you to see what would happen in each case, given the decisions you entered for yourself and the decisions you entered for others.

Stage 2 Practice #1

Suppose you and 4 other members from your group chose ENTER in Stage 1, and therefore, there are a total of 5 active group members. On the screen, please make your investment decision (between 0 and 120 points) and investment decisions for the 4 other active group members. Click SUBMIT when you are done.

You should now see a table on the screen displaying the investments you chose for yourself and the other active members of your group. Below the table, the probability your project succeeds is calculated and labeled "Probability". In this case, when there are a total of 5 active members of your group (including you), the probability that your project succeeds is given by dividing your investment by the sum of the investments from all active group

[29] Added to this paragraph in ND6: "Also, **for these practice decisions only**, the total number of active group members, including you, will be revealed to you. In the actual decision rounds, the total number of active members of your group will not be revealed to you and the project investments for the other active members of your group will be the investments that were actually chosen by the other participants."

members (which includes your investment).

Are there any questions?

Stage 2 Practice #2

Now suppose you and 2 other members from your group chose ENTER in Stage 1, and therefore, there are a total of 3 active group members. On the screen, please make your investment decision (between 0 and 120 points) and investment decisions for the 2 other active group members. Click SUBMIT when you are done.

You should now see a table on the screen displaying the investments you chose for yourself and the other active members of your group. Below the table, the probability your project succeeds is calculated and labeled "Probability". In this case, when there are a total of 3 active members of your group (including you), the probability that your project succeeds is given by dividing your investment by the sum of the investments from all active group members (which includes your investment).

Are there any questions?

Stage 2 Practice #3

Finally, suppose that you are the only member of your group that chose ENTER in Stage 1, and therefore, there is a total of 1 active group member (only you). Since you are the only active member of your group, your project will be successful regardless of the investment you choose. Thus, choosing an investment of 0 allows you to make the largest amount of money when you are the only active member of your group. On the screen, please make your investment decision (between 0 and 120 points). Click SUBMIT when you are done.

You should now see a table on the screen displaying the investment you chose for yourself. Below the table, the probability your project succeeds is calculated and labeled "Probability". In this case, when there is a total of 1 active member of your group (only you), the probability that your project succeeds is always 100%.

Are there any questions?

Remember, in the actual experiment, provided you are active in Stage 2, you will only make your own investment decision. Investment decisions for other active group members, if any, will be made by other participants.[30]

Recap of this part

In each decision round, you will receive an endowment of 120 points. There are two stages.

In Stage 1, you must choose whether you prefer to enter Stage 2, or not enter Stage 2 and receive a fixed payment of 6 points. If you choose ENTER, you will proceed to Stage 2. If you choose NOT ENTER, you will earn the fixed payment of 6 points (in addition to your endowment of 120 points) as your payoff for the round, and will not proceed to Stage 2.

In Stage 2, if you are active, you will decide the size of your project investment (integer number between 0 and 120 points). The total number of active group members (including you) will be shown at the top of the investment decision screen.[31] After the investment decisions are made by active group members, the program will determine the probability your project succeeds, based on the investments made by you and the other active members of you group (if any). If your project succeeds, you earn 120 points in revenue, but if it fails, you earn 0 revenue. Your payoff for the round will be your endowment of 120 points, minus your investment, plus the revenue you earn (120 points if your project succeeds, 0 if it fails).

There will be 41 decision rounds, and at the end of the experiment, you will be paid your earnings from 5 randomly selected rounds.

In a moment, you will start on the actual decision rounds for this part. Please do not communicate with other participants or look at anyone else's monitor. If you have a question or problem, from this point on, please simply raise your hand so that one of us can assist you in private. Please remember to click CONTINUE to proceed.

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[30] Slightly modified in ND6: "Remember, in the actual experiment, the total number of active group members will not be revealed to you at any point. Also, provided you are active in Stage 2, you will only make your own investment decision. Investment decisions for other active group members, if any, will be made by other participants."

[31] ND6: "You will not know the total number of other active group members."