Information disclosure in contests with endogenous entry: An experiment*

Luke Boosey[†] Philip Brookins[‡] Dmitry Ryvkin[§]

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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 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 aggregate investment to be independent of disclosure in all cases. We find empirical entry frequencies decreasing with ω. For aggregate investment, we find no effect of disclosure when ω is low, but a strong positive effect of disclosure when ω is high. The difference is driven by substantial overinvestment in contests with a small, publicly known number of players, contrasted by more restrained investment in contests where the number of players is uncertain and may be small. The behavior under disclosure is explained by a combination of joy of winning and entry regret.

Keywords: contest, endogenous entry, information disclosure, experiment
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[†]Department of Economics, Florida State University, Tallahassee, FL 32306-2180, USA; E-mail: `lboosey@fsu.edu`

[‡]Department of Economics, University of South Carolina, Columbia, SC 29208, USA, Max Planck Institute for Research on Collective Goods, Kurt-Schumacher-Str. 10, D-53113, Bonn, Germany, and Visiting Fellow, Laboratory for Innovation Science at Harvard and Institute for Quantitative Social Science, Harvard University, 1737 Cambridge St., Cambridge, MA 02138, USA; E-mail: `philip.brookins@moore.sc.edu`

[§]Department of Economics, Florida State University, Tallahassee, FL 32306-2180, USA; E-mail: `dryvkin@fsu.edu`

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 and the ensuing design questions regarding disclosure provide the first and most straightforward motivation for our study. Our second 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). Therefore, even in settings where, theoretically, disclosing the number of entrants has no effect on aggregate 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. For example, policy makers can withhold, or make publicly available, information about the participants of a procurement auction or candidates for a state university president position.[1]

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 suitable parameterizations, the

[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.

symmetric equilibrium involves players mixing between entering and not entering the contest with some probability q^*, and both q^* and aggregate 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.

Consistent with theory, we find entry frequencies decreasing in ω. 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 quite 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.

Second, we observe an intriguing difference in subjects' investment behavior across realized group sizes between the low and high outside option settings under disclosure. Consistent with the prior literature, relative overbidding rates are not decreasing in group size when the outside option is low (i.e., when the frequency of entry is high). However, we find a rapid decrease in relative overbidding with group size when the outside option is high and the frequency of entry is low. We show that these differences can be explained well with a behavioral model combining joy of winning and sensitivity to "entry regret," i.e., regret experienced by subjects who forgo the outside option and then lose the contest.

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 with spillovers 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 or duplicative R&D, 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).

Of course, the implications of our results for optimal contest design should be taken with some caution given the stylized nature of our endogenous entry setting and the limited action space – focusing exclusively on disclosure and outside option – we provide for the designer. One important feature of the model we use is that the contest is held, i.e., effectively the prize is handed out for free, even if there is only one participant. This may be unrealistic in some settings, such as a government procurement auction or a sports tournament, which may be canceled if there is not enough competition.[2] However, it is admissible in some contests, where efforts are subject to a minimum quality restriction that can be normalized to zero in our setting. For example, crowdsourcing innovation platforms such as TopCoder or XPRIZE, accept solutions from a single entrant; a qualified candidate would still be hired or promoted when there is a single applicant; and an otherwise indifferent politician can be swayed by a single lobbyist. Another aspect of our model is that we do not allow the designer to restrict the number of participants from above, for example, by means of shortlisting based on preliminary bidding (see, e.g., Fullerton and McAfee, 1999), or by setting a reserve quality (e.g., Liu et al., 2014). While there are certainly other features of the contest that designers may sometimes be able to control, our goal in the present paper is to first understand the implications of disclosure policy for two relatively simple and salient environments – one in which expected entry is high, and one in which expected entry is low.

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, 2019); (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, 2018; Azmat and Möller, 2018).[3]

The contest settings we consider in this paper fall into category (ii), augmented by a variation regarding the disclosure of the number of entrants.[4] For Tullock (1980) contests with exogenous

[2] See, e.g., https://www.transit.dot.gov/funding/procurement/third-party-procurement/single-bid.

[3] 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 (2018).

[4] 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

stochastic entry and the number of entrants following a binomial distribution, Lim and Matros (2009) demonstrate that expected 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), Feng and Lu (2016) and Drugov and Ryvkin (2017) 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 (2019) show that aggregate investment (weakly) increases when the number of players in each group is disclosed.

For a setting with *exogenous stochastic entry*, Boosey, Brookins and Ryvkin (2017) experimentally test the predictions of Lim and Matros (2009) for contests 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.

Within the vast experimental literature on contests (for a review, see Dechenaux, Kovenock and Sheremeta, 2015), we are only aware of a handful of studies exploring endogenous entry behavior by contestants into a single contest. In one of the earlier such studies, 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. Furthermore, consistent with most of the literature (Sheremeta, 2013), substantial overbidding is observed in all treatments.

Other such studies examine the behavior of subjects who must choose between noncompetitive and competitive incentive schemes. For example, Eriksson, Teyssier and Villeval (2009) compare investment behavior across tournaments with either self-selecting or exogenously assigned contestants. In the self-selection treatment, participants must choose between competing in a Lazear-Rosen style tournament or a piece-rate pay scheme. Their data show a selection effect, whereby less risk-averse subjects tend to enter the tournament, resulting in higher overall effort and a decrease in the variance of effort relative to behavior by individuals who were exogenously assigned to the tournament. Similarly, Cason, Masters and Sheremeta (2010) let subjects choose between a noncompetitive piece-rate pay scheme and a competitive setting, which is ei-

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*).

ther a proportional-prize (PP) or a winner-take-all (WTA) Tullock contest. They find that both entry and total performance are higher for the PP contest than for the WTA one. Importantly, endogenous entry does not generate any form of population uncertainty in these studies, since the size of the tournament is always disclosed before investment decisions is made.

Morgan, Orzen and Sefton (2012) and Morgan et al. (2016) study contest entry decisions that are made sequentially in continuous time. In both studies, the number of prior entrants is publicly observable. In the former, the authors manipulate the size of the contest prize and find, consistent with theory, that entry and investment both increase in the prize. However, entry and investment levels are both above (respectively, below) the theoretical predictions when the prize is low (respectively, high). In the latter, Morgan et al. (2016) explore the choice between various outside options and competitive entrepreneurial settings, while varying the degrees of strategic risk and natural risk. In the presence of natural risk, they observe excessive entry and investments, and these findings are further enhanced when the outside option is a gamble. However, as for the studies discussed in the previous paragraph, the number of active competitors is always known to the participants at the time of investment.

In contrast, Hammond et al. (2018) study behavior when bids must be made without knowing the number of entrants. They explore the effect of a prize-augmenting entry fee in all-pay auctions with two potential entrants and private valuations. The principal seeks to maximize expected revenue (equal to the sum of players' investments), with the entry fees collected from the entrants used to augment the value of the prize. While their setup introduces some population uncertainty (there may be one entrant or two entrants), the model and experiment are not designed to study the impact of disclosure on behavior.

Finally, there is also some evidence on behavior in contests with endogenous entry using field data. Liu et al. (2014) compare behavior across a variety of contest settings using data collected by the online crowdsourcing platform Taskcn. The primary goal of their study is to explore how participation and submission quality depend on (i) the size of the winner's prize and (ii) whether or not a high-quality "seed" submission was present during the time of making a contest submission, and if so, whether or not the contestant who submitted the seed solution had a winning history. While increasing the reward increased submission quality, providing a high-quality seed submission decreased entry rates by high-quality contestants, and hence, the overall quality of submissions decreased. While certain elements of disclosure are a natural part of this field environment, the experiment was not designed to systematically vary disclosure policy and study its effects.

As far as we know, the present paper provides the first experimental test of the effects of *information disclosure* in a contest with endogenous entry. A study conceptually closest to ours is by Aycinena and Rentschler (2018) 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 that entry frequencies are affected by the entry fee and that aggregate investment is affected by disclosure in some, but not all cases; however, we do report a positive effect of disclosure on the frequency of entry when the outside option is relatively small.

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),

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

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.[5] Let $q \in [0, 1]$ denote a symmetric entry probability in stage 1. As shown by Lim and Matros (2009),[6] under No Disclosure the unique symmetric equilibrium investment in the second stage is given by the equation

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

As seen from (2), the equilibrium investment is given by the weighted average of equilibrium investments in the contest where the number of players, $(k+1)$, is common knowledge, $x^*_{k+1} = \frac{Vk}{(k+1)^2}$. The weights are equal to the probabilities of different realizations of the number of other entrants, k, from an entrant's perspective. Thus, under Disclosure the entrants' *expected* equilibrium investment is also equal to $x^*(q)$. The *expected* equilibrium payoff of an entrant is, therefore, independent of disclosure and given by the weighted average of payoffs in the contest

[5] In addition to symmetric mixed strategy equilibria we consider here, this game may have asymmetric equilibria; for example, such that some number of players enter for sure while others stay out. Our experimental data do not support any systematic asymmetric equilibrium play, at least with standard money-maximizing preferences. For details, see Appendix C.

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

of $(k+1)$ players, $\pi^*_{k+1} = \frac{V}{(k+1)^2}$:

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

Under Disclosure, the symmetric mixed strategy SPNE with equilibrium entry probability $q^* \in (0,1)$ in stage 1 and investment x^*_{k+1} in stage 2 is determined by the indifference condition $\pi^*(q^*) = \omega$. It can be shown that $\pi^*(q)$ is monotonically decreasing,[7] and hence a unique $q^* \in (0,1)$ exists provided $\pi^*(1) = \frac{V}{n^2} < \omega$ and $\pi^*(0) = V > \omega$. Under No Disclosure, the existence of the symmetric equilibrium with the same entry probability q^* in stage 1 and investment $x^*(q^*)$ in stage 2 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 aggregate 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) 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).[8] Lists for the three measures were presented in a random order. One of

[7] 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.

[8] 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

Treatment	Disclosure	ω	Sessions	Subjects	Groups
D6	Yes	6	3	54	9
D48	Yes	48	3	54	9
ND6	No	6	3	54	9
ND48	No	48	3	54	9
Total			12	216	36

Table 1: Summary of experimental treatments.

the lists, and one of the rows in that list, were selected randomly for actual payments.[9] 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

constructed as the difference between the row numbers where the subject switched in the ambiguous and risky lists.

[9] 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.

according to the contest success function (1). Within each group, only one subject's project could be successful. If the project was successful (respectively, failed) the subject received 120 (respectively, 0) points in revenue for the round. Therefore, including their endowment for the round, a subject who invested x received $240-x$ points 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.[10] 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 payment.

We conducted a total of 12 sessions (eight sessions in November 2017 and four sessions in March 2019) at the XS/FS laboratory at Florida State University. A subject could only participate in one session, and, therefore, only in one treatment. The experimental interface was implemented using z-Tree (Fischbacher, 2007), with subjects making decisions at visually separated computer terminals. A total of 216 subjects (65.28% of them female) were randomly recruited via ORSEE (Greiner, 2015) from a sub-population of FSU students who pre-registered to receive announcements about participation in upcoming experiments. Paper instructions were distributed and read aloud prior to the start of each part. The instructions for Part 2 of the experiment are provided in Appendix D.[11] A session lasted approximately 80 minutes, with subjects earning \$20.02, on average, including a \$7.00 show-up payment.

[10]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 Appendix B, but do not use them in our analysis.

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

5 Results

5.1 Aggregate results

We begin by analyzing average entry frequency and average investment conditional on entry (referred to simply as "investment"), and then also explore two alternative measures of contest investment – total investment and total revenue – that take entry into account and can be of interest from the designer's perspective. Table 2 reports summary statistics for entry and investment across treatments. We compute the average entry and investment using all rounds (1-40) as well as using only the last 15 rounds (26-40).[12] 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 in Table 2. 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.

Given the relatively small number of independent clusters in our data, inference based on asymptotic clustered standard errors may be unreliable. Therefore, throughout the analysis, we rely on nonparametric tests for simple comparisons and on the wild cluster bootstrap method (Cameron, Gelbach and Miller, 2008) for regression analysis. In particular, we report 95% wild cluster bootstrap confidence intervals (instead of standard errors) for summary statistics and all estimates of regression coefficients. Significance levels in regression tables, as well as post-estimation hypothesis tests, are also based on the p-values computed using wild cluster bootstrap.[13]

Entry. The left panel in Figure 1 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).[14] However, many of the comparative static predictions across treatments are consistent with theory as summarized below.

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 vari-

[12] 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.

[13] We adopt the following implementation of wild cluster bootstrap based on the recommendations in Cameron and Miller (2015) and Roodman et al. (2019): For regressions with fewer than 10 clusters, which are those run on data from a single treatment, we use the six-point distribution Webb weights. For regressions that use the data from two treatments (18 clusters) or all four main treatments (36 clusters), we use the default, two-point distribution Rademacher weights. In both cases, we set the number of replications to be 9999.

[14] We use a Wald test comparing the estimated constant in a linear regression to the SPNE prediction. For all treatments, $p < 0.01$.

Treatment	Entry			Investment		
	Rd. 1-40	Rd. 26-40	Predicted	Rd. 1-40	Rd. 26-40	Predicted
D6	0.600	0.572	0.771	37.41	35.43	19.94
	[0.531 0.672]	[0.502 0.643]		[29.03 45.92]	[25.74 45.07]	
D48	0.425	0.374	0.232	44.41	45.66	20.50
	[0.379 0.476]	[0.314 0.438]		[36.11 53.79]	[35.75 56.65]	
ND6	0.526	0.477	0.771	42.93	44.56	19.94
	[0.484 0.566]	[0.417 0.531]		[37.65 48.90]	[38.02 52.89]	
ND48	0.401	0.359	0.232	31.56	28.94	20.50
	[0.347 0.451]	[0.304 0.415]		[25.66 37.39]	[22.36 35.19]	

Table 2: Average entry frequency and average investment by treatment, with 95% wild cluster bootstrap confidence intervals in brackets.

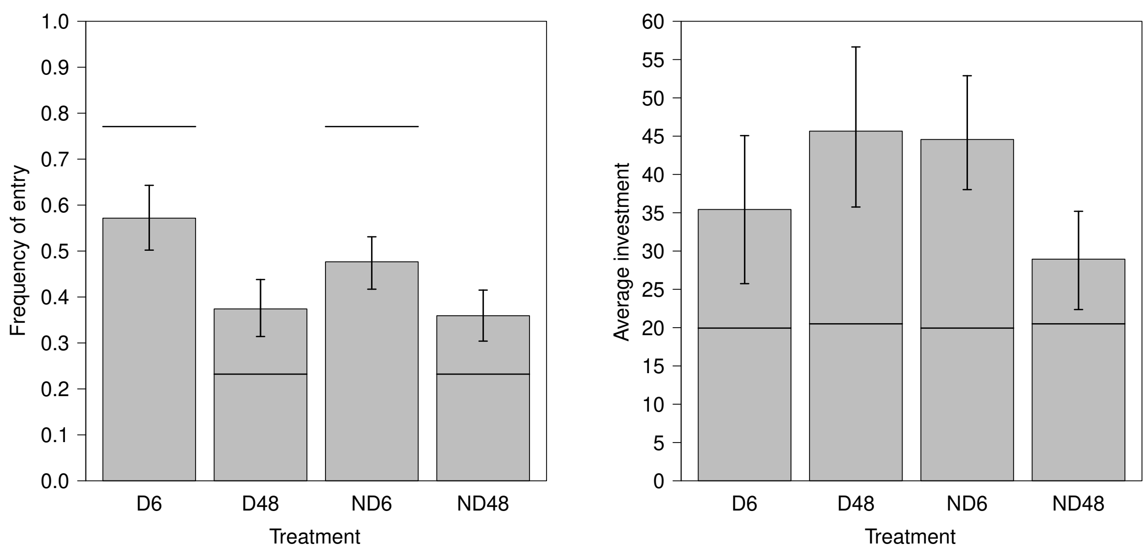

Figure 1: Frequency of entry (left panel) and average investment by treatment (right panel), using data from rounds 26-40. Error bars indicate 95% wild cluster bootstrap confidence intervals. Solid reference lines indicate equilibrium point predictions.

ables. The estimated Probit 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 1, 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.[15] Consistent with theory, we find no significant difference between D48 and ND48 ($p = 0.708$); however, contrary to theory, we find a significantly lower entry frequency in ND6 compared to D6 ($p = 0.026$).[16] These results are also

[15] $p < 0.005$ for both D6 vs. D48 and ND6 vs. ND48, using the Wald test comparing regression coefficients.

[16] Significance results are the same if we use all rounds, with $p = 0.056$ and $p = 0.475$ for $\omega = 6$ and $\omega = 48$

supported by nonparametric Mann-Whitney-Wilcoxon (rank-sum) tests. Using average entry at the group level as the unit of observation, we again find a significant negative effect of entry as ω increases from 6 to 48 for both D (Round 1-40: $p = 0.0001$, Round 26-40: $p = 0.001$) and ND (Round 1-40: $p = 0.0001$, Round 26-40: $p = 0.009$) treatments, and we find no effect of disclosure for $\omega = 48$ (Round 1-40: $p = 0.452$, Round 26-40: $p = 0.723$) and a significantly lower entry frequency in ND compared to D when $\omega = 6$ (Round 1-40: $p = 0.077$, Round 26-40: $p = 0.046$). Finally, we also note that, although there is a significant, negative time trend when we use all rounds, the coefficient on *Period* is not statistically different from zero in 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 when ω is high; however, disclosure has a significant and positive effect on the frequency of entry when ω is low.

These findings are unchanged if we include controls for gender and our elicited measures of risk aversion (RA), ambiguity aversion (AA), and loss aversion (LA).[17] 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 ($p = 0.020$). 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. The right panel in Figure 1 shows average investment levels using data from rounds 26-40 (cf. also Table 2). In all four treatments, average investment is significantly higher than the SPNE prediction, whether we use all rounds or just the last 15 rounds.[18] 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. By comparing the regression coefficients, we find that average investment is significantly higher in ND6 than in ND48 ($p < 0.001$) and significantly higher in D48 than in ND48 ($p = 0.003$), 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 ($p = 0.112$). Similarly, average investment when $\omega = 6$ is higher without disclosure, but the difference is not statistically significant ($p = 0.109$).[19] Furthermore, treatment comparisons remain similar when conducting nonparametric Wilcoxon-Mann-Whitney (rank-sum) tests, as average investment in ND6 and

treatments, respectively.

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

[18] Wald tests using the last 15 rounds: $p = 0.005$ for D6, $p = 0.001$ for D48, $p = 0.001$ for ND6, and $p = 0.016$ for ND48.

[19] Results regarding investment levels do not change when considering all rounds: ND6 vs. ND48 ($p = 0.004$), D48 vs. ND48 ($p = 0.007$), D6 vs. ND6 ($p = 0.227$), and D48 vs. D6 ($p = 0.202$).

	Entry		Investment	
	(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	-0.076*	-0.093**	5.502	9.186
	[-0.151 0.002]	[-0.178 -0.013]	[-3.81 14.93]	[-2.08 20.74]
D48	-0.174***	-0.191***	6.986	10.03
	[-0.254 -0.094]	[-0.283 -0.112]	[-3.90 18.41]	[-2.48 23.23]
ND48	-0.198***	-0.205***	-5.877	-6.489
	[-0.283 -0.118]	[-0.296 -0.130]	[-15.46 3.58]	[-17.32 4.30]
Period	-0.004***	-0.001	-0.0455	0.405*
	[-0.0047 -0.0028]	[-0.0047 0.0027]	[-0.151 0.084]	[-0.075 0.897]
Constant	–	–	38.31***	22.11**
			[30.25 46.34]	[2.85 41.60]
Clusters	36	36	36	36
N	8640	3240	4219	1443

Table 3: Columns (1) and (2) report Probit marginal effects, while columns (3) and (4) report OLS coefficient estimates. 95% wild cluster bootstrap confidence intervals in brackets. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D48 are both significantly higher than in ND48 whether considering the last 15 rounds ($p = 0.002$ and $p = 0.005$, respectively) or all rounds ($p = 0.009$ and $p = 0.019$, respectively), while p-values from rank-sum tests for D6 vs. ND6 and D6 vs. D48 comparisons satisfy $p > 0.10$ when considering all or only the last 15 rounds. 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 (see Section 5.2 below), it does not explain any of the variation in investment decisions by those who enter.

Total investment. Although the preceding analysis has focused on the average investment of entrants only, it can also be useful to compare average *total* investment 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 per-subject investment *without* excluding non-entrants. That is, non-entrants are treated as having invested nothing. For comparison, we add equilibrium point predictions for expected total investment per subject, $q^*x^*(q^*)$, equal to 15.37 for $\omega = 6$ and 4.76 for $\omega = 48$ (independent of disclosure). In all four treatments, average total investment is significantly higher than the SPNE levels.[20] In $\omega = 48$ treatments, this difference is achieved jointly through overbidding by entrants and over-entry. In $\omega = 6$ treatments, overbidding by entrants is offset by under-entry, but these opposing forces combine in such a way that average total investment is still significantly higher than predicted.

We also regress investment (without excluding non-entrants) 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 ($p = 0.006$). Although it is somewhat lower in D48 than in D6, the difference is not significant ($p = 0.313$). Likewise, we find no significant difference between D6 and ND6 ($p = 0.748$). Thus, treatment effects for average total investment are the same as for investment *conditional on entry* summarized 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 in that range of ω. Thus, even in settings where the contest designer is unable to observe the number of entrants (making disclosure impossible), a sufficiently low entry fee can be used to increase total investment. 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.

Total revenue. In our experiment, subjects entering the contest have to forgo the outside option payoff ω. These foregone payments can also be alternatively interpreted as *entry fees* that the designer collects as part of her revenue (see, e.g., Hammond et al., 2018). Figure 3 shows average total revenue per subject defined this way, by treatment. The solid lines represent equilibrium point predictions, $q^*(x^*(q) + \omega)$, equal to 20.00 for $\omega = 6$ and 15.90 for $\omega = 48$.

In all four treatments, when using data from all rounds, average total revenue is significantly higher than predicted (Wald tests: $p = 0.017$ for D6 and $p < 0.01$ for ND6, D48 and ND48). The same holds with data restricted to the last 15 rounds with the exception of D6 where the difference is not significant (Wald test: $p = 0.167$). Following a regression of total revenue on treatment dummies ND6, D48 and ND48, and a time trend, we find that average total revenue is

[20] Wald tests considering data from all or only the last 15 rounds: $p < 0.01$ for all treatments except D6 using the last 15 rounds, where $p = 0.063$.

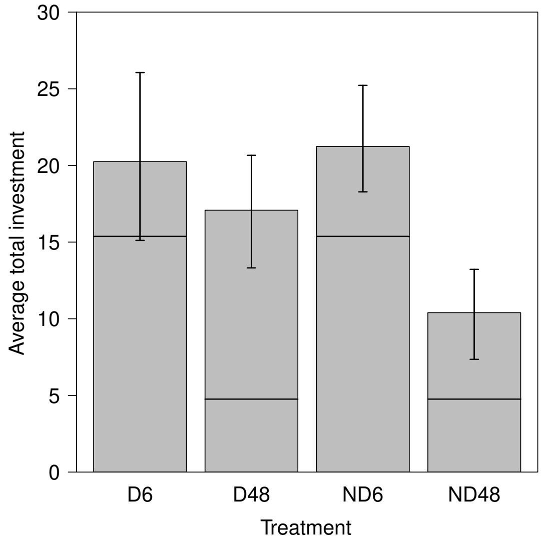

Figure 2: Average total investment by treatment, using rounds 26-40. Error bars indicate 95% wild cluster bootstrap confidence intervals. Solid reference lines indicate equilibrium point predictions.

significantly higher in D48 compared to all other treatments, but no other pairwise comparison across treatments is significant.[21] Thus, disclosure continues to have a large and positive effect on average total revenue defined in this way when $\omega = 48$, but we do not find that increasing the outside option changes average total revenue when the number of players is not disclosed. These results suggest that the designer's revenue is maximized by a combination of restricted entry and disclosure. In contrast, the increase in collected entry fees without disclosure is likely going to be offset by a reduction in entry and entrants' investment.

Payoffs. Finally, we also consider the comparison between payoffs for entrants and non-entrants in each treatment. In equilibrium, these 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 4 compares the average payoff of entrants to the fixed payoff from not entering, for each treatment.[22]

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, and the difference is only significant in ND6 (Wald tests: $p = 0.170$ for D6, $p = 0.011$ for ND6). 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,

[21] Wald tests: $p < 0.005$ for D6 vs. D48 and ND6 vs. D48, $p = 0.038$ for ND48 vs. D48.

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

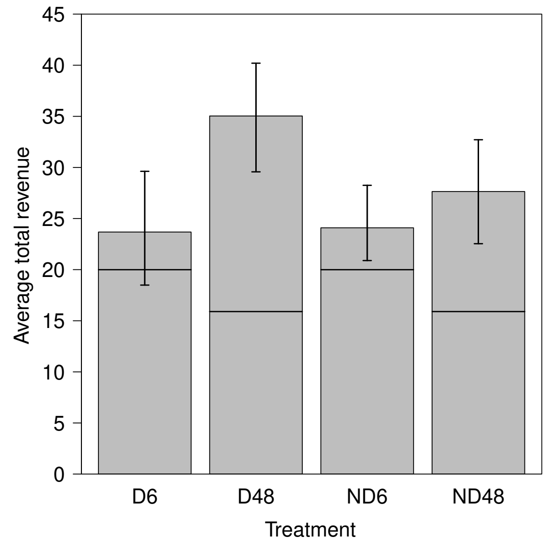

Figure 3: Average total revenue by treatment, using rounds 26-40. Error bars indicate 95% wild cluster bootstrap confidence intervals. Solid reference lines indicate equilibrium point predictions.

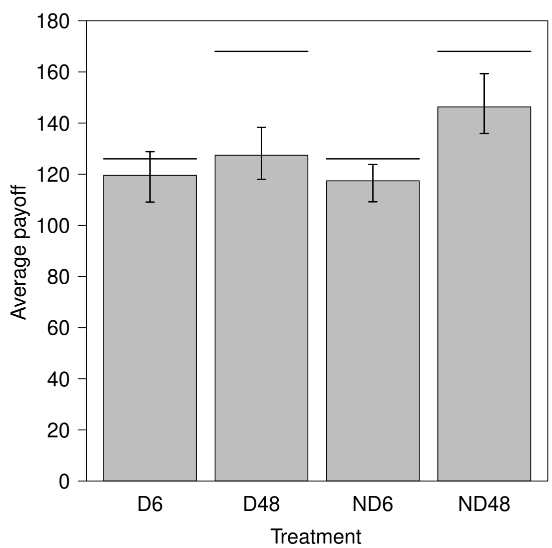

Figure 4: Average payoff for entrants, by treatment, using rounds 26-40. Solid reference lines indicate the (fixed) payoff for non-entrants. Error bars indicate 95% wild cluster bootstrap confidence intervals.

significantly less than the payoff of a non-entrant (Wald tests: $p < 0.001$ for D48, $p = 0.007$ for ND48). In this case, the dual departures from equilibrium in entry and investment decisions reinforce one another to lower average payoffs of entrants.

	$\omega = 6$	$\omega = 48$
Enter_t	(1)	(2)
NDω	0.152	0.056
	[-0.064 0.358]	[-0.288 0.322]
RA	-0.002	-0.018**
	[-0.017 0.015]	[-0.030 -0.004]
RA×NDω	-0.028**	-0.004
	[-0.052 -0.002]	[-0.032 0.029]
Period	-0.005*	0.003
	[-0.0100 0.0004]	[-0.002 0.008]
Constant	0.748***	0.454***
	[0.490 1.009]	[0.200 0.726]
Clusters	18	18
N	1620	1620

Table 4: Linear probability model regression results of entry on risk aversion, using rounds 26-40. Column (1) compares D6 and ND6 (with D6 the omitted dummy), while Column (2) compares D48 and ND48 (with D48 the omitted dummy). 95% wild cluster bootstrap confidence intervals in brackets. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 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 (RA×NDω), and a time trend. Thus, the estimated effect of risk aversion on entry is captured by the coefficient estimate on RA for Dω, and by the sum of coefficient estimates on RA and RA×NDω for NDω. Column (1) compares D6 and ND6. In this case, we observe no effect of risk aversion in D6 (Wald test: $p = 0.787$), but a significantly negative effect of risk aversion on entry in ND6 (Wald test: $p = 0.030$). 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 reduces entry in D48 but not in ND48 (Wald tests: $p = 0.019$ for D48, $p = 0.156$ for ND48).

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, but only when the number of entrants **is** *disclosed.*

These findings show that risk aversion affects entry in different ways, depending on the outside option and disclosure rule. 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.[23]

5.3 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 5 shows the average investment, broken down by the number of entrants, m, in the contest, for each of the four treatments. First, we examine the ND treatments, shown in the bottom two panels of Figure 5. As expected, there is no evidence that average investment declines in the realized number of entrants in ND6 and ND48 (estimated slope of -0.38, $p = 0.913$, and +2.64, $p = 0.241$, respectively). The bars at $m = 1$ in ND6 and at $m = 5$ in ND48 may seem like significant outliers, but they are based on too few observations (less than 3% in both cases) to contribute statistically. In the latter case, the bar is based on observations from one group only, and hence the confidence interval cannot be evaluated. However, average investment in ND48 is lower than in ND6 for each realized number of entrants ($p < 0.05$ in all cases except $m = 5$ where observations in ND48 are based on one group). 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

[23] To further explore the effects of risk preferences on behavior in the disclosure treatments, we computed equilibrium predictions in two models with risk-averse agents: (i) with homogeneously risk-averse agents and (ii) with heterogeneous agents whose risk preferences are their private information. In the model with homogeneous agents, in equilibrium, both entry and expected investment are below the risk-neutral predictions; thus, homogeneous risk-aversion cannot explain our findings. The model with private and heterogeneous risk preferences does produce the selection effect of risk-aversion on entry, leading to a cutoff equilibrium where sufficiently risk-tolerant players enter the contest and others stay out. This result is similar to the one identified theoretically by Pevnitskaya (2004) and confirmed experimentally by Palfrey and Pevnitskaya (2008) for first-price auctions. However, this model still does not explain the differential effects of risk-aversion on entry across ω. More details are available from the authors upon request.

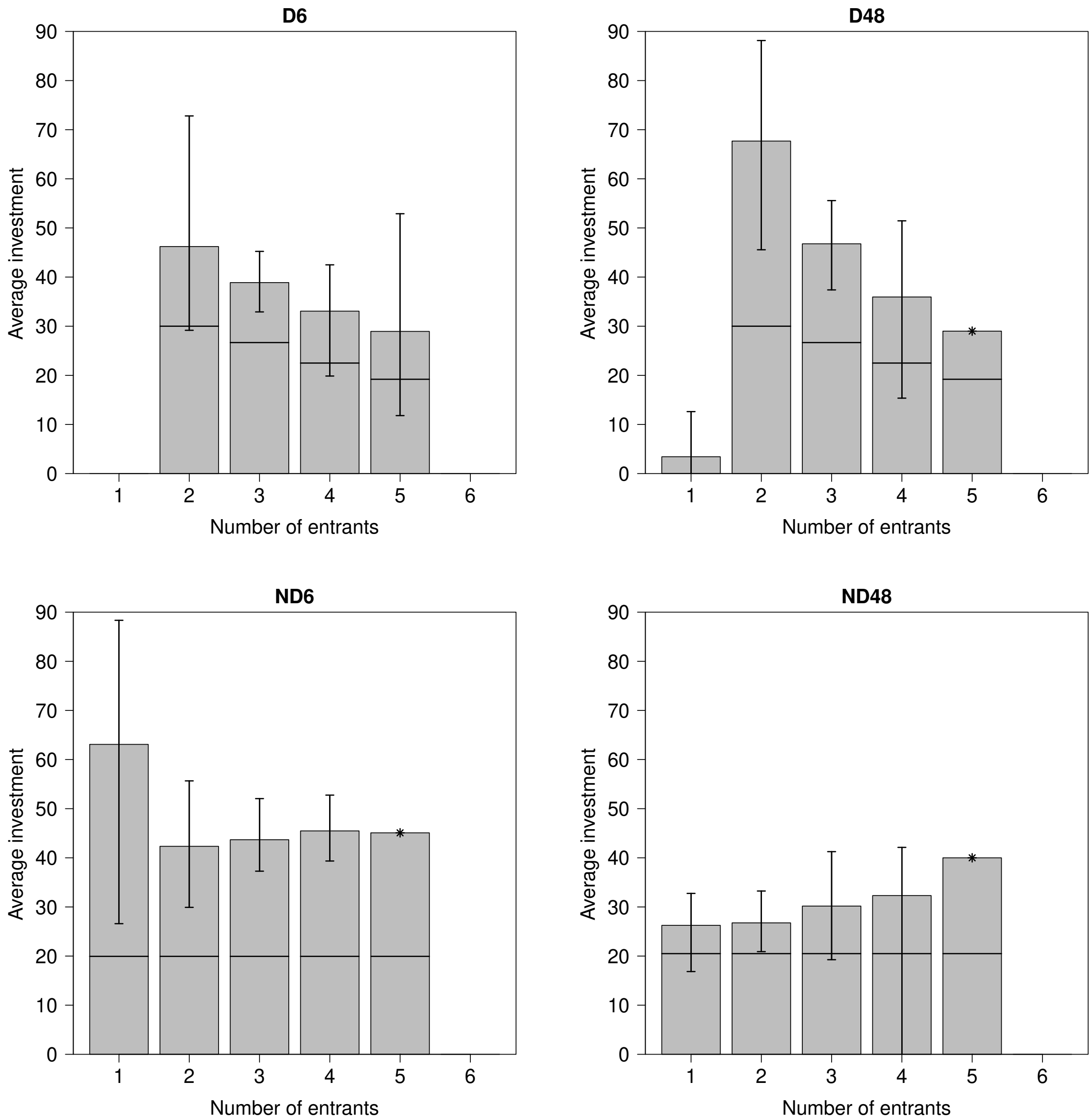

Figure 5: Average investment by number of entrants by treatment, using rounds 26-40. Error bars indicate 95% wild cluster bootstrap confidence intervals. The confidence interval is replaced with an asterisk ($*$) in the one instance where it cannot be evaluated due to too few observations. Note that the lower bound of the confidence interval for ND48 when there are 4 entrants is -10.74. Solid reference lines indicate equilibrium point predictions.

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 5. As predicted, average investment in D6 and D48 indeed varies systematically with the realized 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.[24] Second, when there are at least two entrants, average investment is decreasing in the number of entrants m, 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 m is relatively weak (estimated slope of -5.47, $p = 0.338$).[25] Overbidding is observed for all $m \geq 2$, with the rate of overbidding around 50% and not decreasing in the number of entrants,[26] consistent with the meta-analysis of Sheremeta (2013). In contrast, in D48 the decline in average investment with respect to the number of entrants is strong and significant (estimated slope of -15.08, $p = 0.009$), and overbidding is decreasing in m (both in absolute terms and, although not significantly, as a rate, with $p = 0.029$ and $p = 0.108$, respectively). The rate of overbidding is extremely high when the number of entrants is small (125% for $m = 2$ and 75% for $m = 3$), and reduces to about 50% for $m = 5$.

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 m, average investment levels in these contests are in line with the levels observed in the same size contests without entry. Thus, in D6 our entrants' behavior conditional on group size is consistent with the existing 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 $m = 2$ for D48.[27] On the other hand, when the realized number of entrants is higher ($m = 3, 4$ or 5), the effect of a strong desire to win is countered by the lower likelihood of winning. The observed decline in overbidding rates with group size in D48 is in stark contrast with the experimental literature on contests without entry, and is largely driven by substantial overbidding behavior when the group size is relatively small ($m = 2$ or 3). Interestingly, the degree of overbidding when $m = 5$ is statistically indistinguishable between D6 and D48, suggesting that behavioral responses in that case are similar across treatments.

Subjects who enter the contest in D48 likely do so with the hope that realized group size

[24] In D48, there were 35 instances where only one player entered, and the entrant invested zero in 34 of those instances. In D6, due to the higher frequency of entry, there are no observations where only one player entered.

[25] However, average investment can be fitted fairly well with function $x^*_m = \frac{V(m-1)}{m^2}$, cf. Section 3. An OLS regression of individual investment on x^*_m without intercept produces slope estimate 1.48 ($p < 0.001$), indicating overbidding by about 50%, on average.

[26] Average investment is 54.0% higher than equilibrium for $m = 2$, 45.8% higher for $m = 3$, 47.0% higher for $m = 4$, and 50.8% higher for $m = 5$.

[27] 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.

will be small ($m = 1$ 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.

Deviations from money-maximizing equilibrium behavior can broadly be attributed to two classes of reasons: bounded rationality and behavioral phenomena. In the following two sections, we attempt to explain the observed deviations using a representative model from each class. We show that Quantal Response Equilibrium (QRE) captures deviations in entry frequencies very well, but cannot explain the observed bidding behavior of entrants. We then construct a behavioral model of bidding in treatments with disclosure based on a combination of joy of winning and entry regret.

5.4 Explaining behavior using QRE

A subject making completely random entry decisions would enter the contest with probability 0.5 regardless of parameters. Consider entry behavior in the disclosure treatments D6 and D48. While the SPNE entry frequency is relatively high (0.771) for $\omega = 6$ and low (0.232) for $\omega = 48$, the observed frequencies (0.571 and 0.374, 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 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

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

where $\mu \in [0, \infty)$ represents the inverse of the level of "noise," or errors in players' decision making. As $\mu \to 0$, behavior becomes completely random, with $p(s) \to \frac{1}{|S|}$, whereas in the opposite limit, $\mu \to \infty$, 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) and Morgan et al. (2016) compute the symmetric subgame-perfect QRE entry probabilities for their sequential 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* stages of the game,

	Entry			Investment		
Treatment	SPNE	Observed	QRE	SPNE	Observed	QRE
D6	0.771	0.571	0.534	19.94	35.43	29.64
D48	0.232	0.374	0.356	20.50	45.66	51.36
ND6	0.771	0.477	0.536	19.94	44.56	29.52
ND48	0.232	0.360	0.356	20.50	28.94	51.48

Table 5: Entry and investment SPNE predictions, observed averages for rounds 26-40, and QRE predictions for $\hat{\mu} = 0.6$, by treatment.

and hence, obtain QRE predictions for both entry and subsequent investment behavior.[28]

We relegate the full technical details of our approach to Appendix A. However, two key features are worth emphasizing. First, as already mentioned, for the Disclosure setting we use a full two-stage formulation of QRE, where at 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 μ that provides the best fit for the resulting eight averages (cf. Table 2). This task is complicated by the fact that, for any μ, the equilibrium payoffs scale with ω, such that the sensitivity to μ 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 μ 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 $\hat{\mu} = \mu\omega$ 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 $\hat{\mu} = 0.6$.

Table 5 reports, for each treatment, the predicted entry and investment according to QRE with $\hat{\mu} = 0.6$, 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

[28] 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.

cannot explain the patterns of investment. While QRE does capture the overbidding observed in all treatments, and the observation that investment in D48 is significantly higher than in D6, it does not explain why we observe higher investment levels in ND6 compared to ND48, which contradicts the SPNE comparative static. As discussed earlier, this difference is due to the effect of the probability of being alone in the contest on overbidding.

5.5 Explaining investment behavior in D6 and D48

As discussed in section 5.3, the patterns of entrants' investment in D6 are generally consistent with the prior experimental literature on contests, as we observe stable overbidding and a relatively weak decline in investment with contest size m. In contrast, in D48, investment behavior is quite different across realized contest sizes, as we observe very substantial overbidding for $m = 2$, but a strong decline as the number of entrants increases, eventually converging to approximately the same overbidding rate as in D6 when $m = 5$. These differences in post-entry investment between D6 and D48 are rather striking considering that *conditional on the number of entrants investment should be exactly the same* in the two treatments. In what follows, we propose a simple behavioral model which explains these findings surprisingly well.

The model is based on a combination of three ideas and, as we show, ends up being isomorphic to a standard model of regret. First is the idea of "rationalizing the past" or "taste for consistency" (Eyster, 2002). In a two-period model, Eyster (2002) shows that if in period 1 the decision maker (DM) chose an action, then in period 2 the DM will tend to choose an action that is consistent with the period 1 choice being optimal *ex post*, even if in reality it is not. In application to our setting, if a player enters the contest and then realizes she made a mistake (i.e., there are too many entrants, and there is no way to earn more than the forgone outside option), the player will choose an investment that is in some way consistent with entry being optimal. This is modeled using a regret function where the best alternative – in our case, ω – is treated as a reference point. Second is the assumption that individuals tend to be loss-averse (Kahneman and Tversky, 1979): the marginal disutility from a loss is higher than or equal to the marginal utility from a gain near a reference point.[29] Lastly, in order to account for the overbidding we observe across treatments, we augment the monetary value of winning V with a "joy of winning" parameter, $w \geq 0$, so that the total value of winning becomes $\tilde{V} = V(1 + w)$. Following Boosey, Brookins and Ryvkin (2017), we assume individuals exhibit "constant winning aspirations" (CWA); that is, w depends on the contest size m in such a way that the expected equilibrium nonmonetary utility gained from winning, $\frac{w}{m}$, is held constant across contest sizes, i.e., $\frac{w}{m} = W > 0$, where W is a parameter.

We write player i's utility in the form

$$u_i = \tilde{V} p_i - x_i + \eta[p_i(\tilde{V} - x_i - \omega) + \lambda(1 - p_i)(-x_i - \omega)]. \quad (5)$$

[29] Behavior in Tullock contests with loss aversion has been studied by Cornes and Hartley (2012) and Kong (2008); however, both assume a reference point of zero.

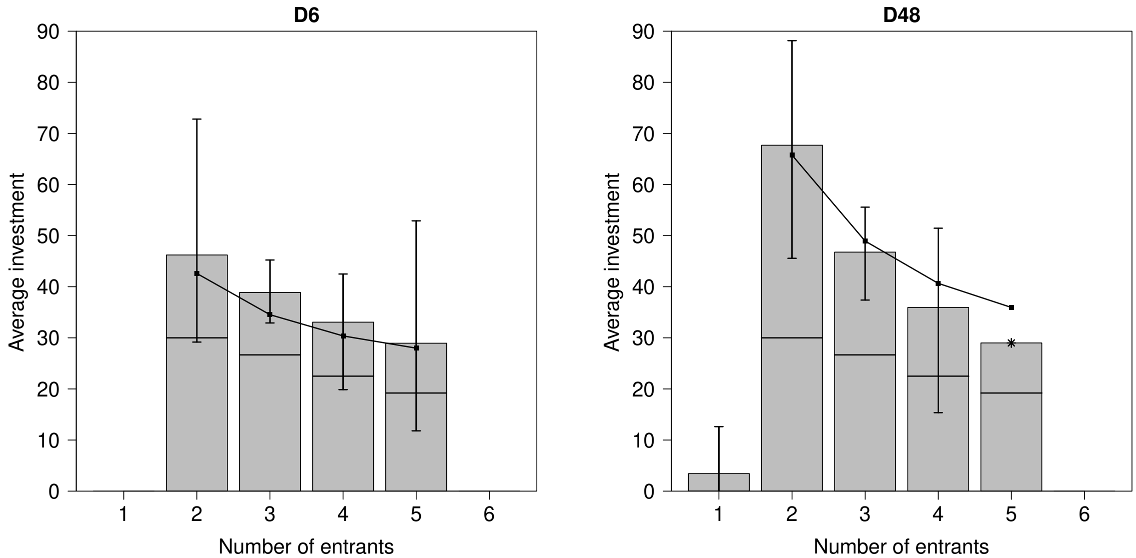

Figure 6: Average investment by number of entrants in D6 (left panel) and D48 (right panel), using data from rounds 26-40. Error bars indicate 95% wild cluster bootstrap confidence intervals. Horizontal reference lines indicate SPNE point predictions, and solid squares indicate behavioral predictions $x^*_m(\tilde{\eta}, W)$ with parameters $W = 0.96$, $\tilde{\eta} = 4.92$.

Here, p_i is the probability of player i winning the contest of m players given by (1). The first part is the standard payoff function, except $\tilde{V}$ includes joy of winning. Parameter $\eta \geq 0$ determines the weight of the behavioral component. The first part in brackets represents a gain in utility in the case of winning, and the second part represents a loss in the case of losing, relative to ω. The loss aversion parameter is $\lambda \geq 1$.

Via an affine transformation $\tilde{u}_i = \frac{u_i + \eta\omega}{1+\eta}$, utility (5) can be cast in the form

$$\tilde{u}_i = \tilde{V} p_i - x_i + \tilde{\eta}(1 - p_i)(-x_i - \omega). \tag{6}$$

Here, $\tilde{\eta} = \frac{\eta(\lambda-1)}{1+\eta}$ is the renormalized loss parameter. Model (6) is similar to standard models of regret where the player experiences disutility if her choice leads to a payoff below the best alternative option.[30] Specifically, a player experiences "entry regret" in the event she enters the contest and loses, because her best alternative payoff, ω, exceeds the payoff from losing, $-x_i$, and could have been obtained with certainty had she chosen not to enter.

Differentiating with respect to x_i, setting the derivative equal to zero, and solving for the symmetric equilibrium investment $x_i = x^*$ for all i, obtain

$$x^*_m(W, \tilde{\eta}) = \frac{m-1}{m^2} \frac{V(1 + mW) + \tilde{\eta}\omega}{1 + \frac{\tilde{\eta}(m-1)^2}{m^2}}. \tag{7}$$

[30] See, e.g., Loomes and Sugden (1982); Filiz-Ozbay and Ozbay (2007). Morgan et al. (2016) use a similar model to explain behavior in their sequential entry contest game.

	D6, D48	D6, D16, D48	
Parameters	(1)	(2)	(3)
W	0.963**	1.001**	0.963***
	(0.289)	(0.328)	(0.284)
$\tilde{\eta}$	4.918**	4.523**	4.918**
	(1.892)	(1.923)	(1.850)
W_1			0.864
			(1.473)
$\tilde{\eta}_1$			2.738
			(7.414)
R^2	0.992	0.986	0.993
N	8	12	12

Table 6: Nonlinear least squares regression results for Eq. (7) as a function of ω and $m \geq 2$, using average investment data from rounds 26-40. Column (1) fits Eq. (7) with two parameters, $\tilde{\eta}$ and W, using data from D6 and D48. Column (2) does the same using data from D6, D16 and D48. Column (3) fits the model using data from D6, D16 and D48 and allowing for W and $\tilde{\eta}$ to be different in D16. Standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

It is straightforward to see that when $\tilde{\eta} = 0$ (i.e., when $\eta = 0$ or $\lambda = 1$) and $W = 0$, we have $x_m^*(0,0) = x_m^* = \frac{(m-1)V}{m^2}$ as in the standard contest model. For $W, \tilde{\eta} > 0$, relative overbidding $\frac{x_m^*(W,\tilde{\eta})}{x_m^*}$ may be increasing, decreasing, or nonmonotone in m, but the slope of relative overbidding as a function of m is unambiguously decreasing in ω.

Figure 6 shows average investment across realized contest size for D6 (left panel) and D48 (right panel), equilibrium predictions from the standard model (horizontal solid lines), and predictions $x_m^*(\tilde{\eta}, W)$ (connected solid squares). Parameter values $\tilde{\eta} = 4.92$ ($SE = 1.89$) and $W = 0.96$ ($SE = 0.29$) have been obtained by fitting Eq. (7) with nonlinear least squares to the empirical average investment in D6 and D48 as a function of ω and m, for $m \geq 2$. The regression results are shown in column (1) of Table 6. As seen from Figure 6, the behavioral predictions fit our data quite well, capturing the difference between D6 and D48 in overall investment levels and slopes with respect to m.

Model (6) combines two behavioral components – joy of winning and entry regret. It is easy to see that each of these components plays a critical role in explaining investment behavior in D6 and D48; in other words, the model is rather parsimonious, and a model with any one of the two components would completely miss an important feature of the dependence of investment on m in the two treatments. Joy of winning alone can explain overbidding, but it would generate the same levels of overbidding in D6 and D48, and the same slope of investment with respect to m. Entry regret alone can explain the difference in slopes, but it would not explain overbidding.

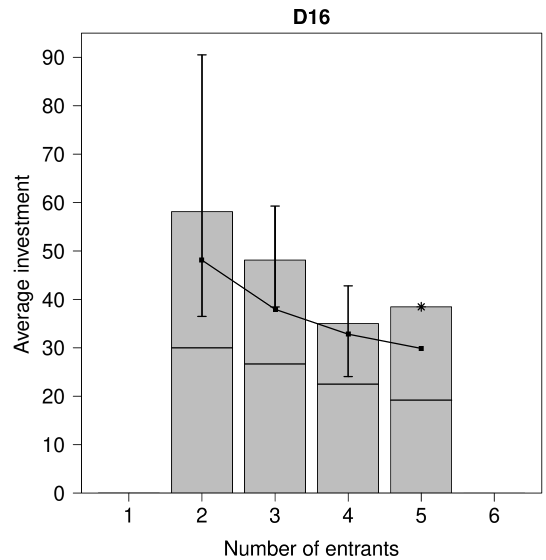

Figure 7: Average investment by number of entrants in D16, using data from rounds 26-40. Error bars indicate 95% wild cluster bootstrap confidence intervals. Horizontal reference lines show SPNE point predictions, and solid squares show *out-of-sample* behavioral predictions $x^*(W, \tilde{\eta})$ with parameters $W = 0.96$, $\tilde{\eta} = 4.92$ calibrated on D6 and D48 data.

5.6 Out-of-sample validation of the behavioral model

Parameter estimates from the behavioral model presented in the previous section were obtained using data from D6 and D48 treatments, and thus the fit we observe in Figure 6 shows that the model *explains* data quite well. It is not clear, however, to what extent the model can *predict* behavior out-of-sample. In order to assess that, we collected data in a new disclosure treatment where we used a new outside option of $\omega = 16$.[31] In this new treatment, referred to as D16, theory predicts an entry frequency of $q^* = 0.497$ and expected investment $x^*(q^*) = 23.60$. We chose $\omega = 16$ as it was the closest integer generating an entry frequency close to 50%, which is approximately the midpoint prediction between D6 ($q^* = 0.771$) and D48 ($q^* = 0.232$).

Next, we check how the behavioral model with parameters obtained using data from treatments D6 and D48 predicts behavior in D16. Figure 7 shows average investment by group size for D16, along with the behavioral predictions. While a bit worse than in Figure 6, the fit is still pretty good. Most importantly, the out-of-sample prediction captures the main features of the D16 data as compared to the other two treatments: The level of overbidding as well as the slope with respect to the number of entrants are in between D6 and D48. The average investment for $m = 5$ may seem like an outlier, but that bar is only based on observations from two groups (and 4% of the total number of observations), and its standard error cannot be estimated reliably.

For comparison, column (2) in Table 6 shows the results of the same nonlinear least squares

[31] We ran three sessions of this treatment in March 2019, each consisting of 18 subjects, 57.4% of them female, producing 9 independent groups. Average earnings including the \$7 show-up payment were \$18.85. The experimental design and procedures were otherwise identical to the ones described in Section 4.

regression as in column (1), but using data from all three treatments (D6, D16 and D48). The addition of D16 data does not lead to any substantial changes in the coefficient estimates.

A more rigorous statistical test for how well the model with parameter values calibrated on the data from D6 and D48 fits the behavior in D16 is presented in column (3) of Table 6. Here, we show parameter estimates from a nonlinear least squares regression of $x^*_m(W, \tilde{\eta})$ on ω and $m \geq 2$ using data from all three treatments (D6, D16 and D48), and allowing parameters W and $\tilde{\eta}$ to be different in D16. That is, we replace W with $W + W_1 \cdot D16$ and $\tilde{\eta}$ with $\tilde{\eta} + \tilde{\eta}_1 \cdot D16$, where W_1 and $\tilde{\eta}_1$ are new parameters and $D16$ is a dummy equal 1 in D16 and zero otherwise. As seen from the regression, the new parameters are not statistically significant (the Wald test for their joint significance produces $p = 0.196$), which implies there is no evidence that the parameter values are different in D16.[32] It is worth noting that the estimates of W_1 and $\tilde{\eta}_1$, although far from being statistically significant, are quite large. Thus, the fit is not ideal; however, given that we are fitting behavior in a between-subject treatment out-of-sample, we conclude that, on balance, the model performs very well.

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.[33] 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 implications of our results for policy and contest design 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.

[32] Of course, the choice of D16 for out-of-sample fitting is arbitrary. We performed a similar exercise using D16 and D48 for the baseline data and fitting D6 out-of-sample. The results are even more convincing, with $p = 0.991$ for the joint significance of the interaction terms. However, when we use D6 and D16 for the baseline data and try to fit D48 out-of-sample, the fit is worse: While $p = 0.207$ for the joint significance of the interactions, the estimates of W and $\tilde{\eta}$ are not individually significant as well (they are, however, significant jointly at $p = 0.025$). This is not very surprising because D6 and D16 are relatively close in terms of ω, while D48 is rather far from them both. Predicting D48 behavior with calibration from D6 and D16 would be challenging for any model.

[33] 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.

While we maintain that our results are quite informative regarding optimal contest design, there is still scope for a richer analysis. In our experiment, we focus on a stylized setting for which the disclosure policy and the outside option (or entry fee) are the principal design features that may be varied. Yet, there are contest environments in which the contest designers have at their disposal a number of additional tools with which to encourage or limit the entry and investment decisions of potential participants. Such additional features provide a rich set of opportunities for extending our study to further understand the optimal design of contests with endogenous entry.

Finally, given that many of 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[34] and the prevalence of unrealistic expectations regarding career success in athletics or the arts.[35] Given how widespread, and well-documented, overbidding 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.

References

Anderson, Lisa R., and Sarah L. Stafford. 2003. "An experimental analysis of rent seeking under varying competitive conditions." *Public Choice*, 115(1-2): 199–216.

Aoyagi, Masaki. 2010. "Information feedback in a dynamic tournament." *Games and Economic Behavior*, 70(2): 242–260.

Aycinena, Diego, and Lucas Rentschler. 2018. "Auctions with endogenous participation and an uncertain number of bidders: experimental evidence." *Experimental Economics*, 21(4): 924–949.

Azmat, Ghazala, and Marc Möller. 2009. "Competition among contests." *The RAND Journal of Economics*, 40(4): 743–768.

Azmat, Ghazala, and Marc Möller. 2018. "The distribution of talent across contests." *Economic Journal*, 128(609): 471–509.

[34] 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

[35] 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.

Boosey, Luke, Philip Brookins, and Dmitry Ryvkin. 2017. "Contests with group size uncertainty: Experimental evidence." *Games and Economic Behavior*, 105: 212–229.

Boosey, Luke, Philip Brookins, and Dmitry Ryvkin. 2019. "Contests between groups of unknown size." *Games and Economic Behavior*, 113: 756–769.

Brookins, Philip, and Dmitry Ryvkin. 2014. "An experimental study of bidding in contests of incomplete information." *Experimental Economics*, 17(2): 245–261.

Cameron, A Colin, and Douglas L Miller. 2015. "A practitioner's guide to cluster-robust inference." *Journal of Human Resources*, 50(2): 317–372.

Cameron, A Colin, Jonah B Gelbach, and Douglas L Miller. 2008. "Bootstrap-based improvements for inference with clustered errors." *The Review of Economics and Statistics*, 90(3): 414–427.

Cason, Timothy N., William A. Masters, and Roman M. Sheremeta. 2010. "Entry into winner-take-all and proportional-prize contests: An experimental study." *Journal of Public Economics*, 94(9-10): 604–611.

Cornes, Richard, and Roger Hartley. 2012. "Loss aversion in contests." *University of Manchester*.

Dechenaux, Emmanuel, Dan Kovenock, and Roman M. Sheremeta. 2015. "A survey of experimental research on contests, all-pay auctions and tournaments." *Experimental Economics*, 18(4): 609–669.

Deck, Cary, and Erik O. Kimbrough. 2017. "Experimenting with Contests for Experimentation." *Southern Economic Journal*, 84(2): 391–406.

Denter, Philipp, John Morgan, and Dana Sisak. 2014. "'Where Ignorance is Bliss,'Tis Folly to Be Wise': Transparency in Contests." *Working paper, Available at SSRN:*. http://dx.doi.org/10.2139/ssrn.1836905.

DiPalantino, Dominic, and Milan Vojnovic. 2009. "Crowdsourcing and all-pay auctions." 119–128, ACM.

Drugov, Mikhail, and Dmitry Ryvkin. 2017. "Winner-take-all tournaments." *CEPR Discussion Working Paper No. DP12067*. https://ssrn.com/abstract=2980827.

Dunne, Timothy, Mark J. Roberts, and Larry Samuelson. 1989. "The growth and failure of US manufacturing plants." *The Quarterly Journal of Economics*, 104(4): 671–698.

Dyer, Douglas, John H. Kagel, and Dan Levin. 1989. "Resolving uncertainty about the number of bidders in independent private-value auctions: an experimental analysis." *The RAND Journal of Economics*, 20(2): 268–279.

Ederer, Florian. 2010. "Feedback and motivation in dynamic tournaments." *Journal of Economics & Management Strategy*, 19(3): 733–769.

Epstein, Gil S, and Yosef Mealem. 2013. "Who gains from information asymmetry?" *Theory and Decision*, 75(3): 305–337.

Eriksson, Tor, Sabrina Teyssier, and Marie-Claire Villeval. 2009. "Self-selection and the efficiency of tournaments." *Economic Inquiry*, 47(3): 530–548.

Eyster, Erik. 2002. "Rationalizing the past: A taste for consistency." *Nuffield College Mimeograph.*

Feng, Xin, and Jingfeng Lu. 2016. "The optimal disclosure policy in contests with stochastic entry: A Bayesian persuasion perspective." *Economics Letters*, 147: 103–107.

Filiz-Ozbay, Emel, and Erkut Y Ozbay. 2007. "Auctions with anticipated regret: Theory and experiment." *American Economic Review*, 97(4): 1407–1418.

Fischbacher, Urs. 2007. "z-Tree: Zurich toolbox for ready-made economic experiments." *Experimental Economics*, 10(2): 171–178.

Fullerton, Richard L., and R. Preston McAfee. 1999. "Auctionin entry into tournaments." *Journal of Political Economy*, 107(3): 573–605.

Fu, Qiang, and Jingfeng Lu. 2010. "Contest design and optimal endogenous entry." *Economic Inquiry*, 48(1): 80–88.

Fu, Qiang, Qian Jiao, and Jingfeng Lu. 2011. "On disclosure policy in contests with stochastic entry." *Public Choice*, 148(3-4): 419–434.

Fu, Qiang, Qian Jiao, and Jingfeng Lu. 2015. "Contests with endogenous entry." *International Journal of Game Theory*, 44(2): 387–424.

Garland, Howard, and Stephanie Newport. 1991. "Effects of absolute and relative sunk costs on the decision to persist with a course of action." *Organizational Behavior and Human Decision Processes*, 48(1): 55–69.

Goeree, Jacob K, Charles A Holt, and Thomas R Palfrey. 2002. "Quantal response equilibrium and overbidding in private-value auctions." *Journal of Economic Theory*, 104(1): 247–272.

Gradstein, Mark. 1995. "Intensity of competition, entry and entry deterrence in rent seeking contests." *Economics & Politics*, 7(1): 79–91.

Greiner, Ben. 2015. "Subject pool recruitment procedures: organizing experiments with ORSEE." *Journal of the Economic Science Association*, 1(1): 114–125.

Halac, Marina, Navin Kartik, and Qingmin Liu. 2017. "Contests for experimentation." *Journal of Political Economy*, 125(5): 1523–1569.

Hammond, Robert G, Bin Liu, Jingfeng Lu, and Yohanes E Riyanto. 2018. "Enhancing effort supply with prize-augmenting entry fees: Theory and experiments." *International Economic Review*.

Harbring, Christine, and Bernd Irlenbusch. 2011. "Sabotage in tournaments: Evidence from a laboratory experiment." *Management Science*, 57(4): 611–627.

Harstad, Ronald M., John H. Kagel, and Dan Levin. 1990. "Equilibrium bid functions for auctions with an uncertain number of bidders." *Economics Letters*, 33(1): 35–40.

Heijnen, Pim, and Lambert Schoonbeek. 2017. "Signaling in a Rent-Seeking Contest with One-Sided Asymmetric Information." *Journal of Public Economic Theory*, 19(2): 548–564.

Higgins, Richard S, William F Shughart, and Robert D Tollison. 1985. "Efficient rents 2 free entry and efficient rent seeking." *Public Choice*, 46(3): 247–258.

Holt, Charles A., and Susan K. Laury. 2002. "Risk aversion and incentive effects." *American Economic Review*, 92(5): 1644–1655.

Hurley, Terrance M, and Jason F Shogren. 1998*a*. "Asymmetric information contests." *European Journal of Political Economy*, 14(4): 645–665.

Hurley, Terrance M, and Jason F Shogren. 1998*b*. "Effort levels in a Cournot Nash contest with asymmetric information." *Journal of Public Economics*, 69(2): 195–210.

Isaac, R. Mark, Svetlana Pevnitskaya, and Kurt S. Schnier. 2012. "Individual behavior and bidding heterogeneity in sealed bid auctions where the number of bidders is unknown." *Economic Inquiry*, 50(2): 516–533.

Ivanova-Stenzel, Radosveta, and Timothy C. Salmon. 2004. "Bidder preferences among auction institutions." *Economic Inquiry*, 42(2): 223–236.

Kahana, Nava, and Doron Klunover. 2015. "A note on Poisson contests." *Public Choice*, 165(1-2): 97–102.

Kahana, Nava, and Doron Klunover. 2016. "Complete rent dissipation when the number of rent seekers is uncertain." *Economics Letters*, 141: 8–10.

Kahneman, Daniel, and Amos Tversky. 1979. "Prospect theory: An analysis of decisions under risk." *Econometrica*, 47: 278.

Kaplan, Todd R, and Aner Sela. 2010. "Effective contests." *Economics Letters*, 106(1): 38–41.

Klein, Arnd Heinrich, and Armin Schmutzler. 2017*a*. "Incentives and motivation in dynamic contests." *Unpublished manuscript.*

Klein, Arnd Heinrich, and Armin Schmutzler. 2017*b*. "Optimal effort incentives in dynamic tournaments." *Games and Economic Behavior*, 103: 199–224.

Kong, Xiaojing. 2008. "Loss aversion and rent-seeking: An experimental study." CeDEx discussion paper series.

Konrad, Kai A, and Dan Kovenock. 2012. "The lifeboat problem." *European Economic Review*, 56(3): 552–559.

Kovenock, Dan, Florian Morath, and Johannes Münster. 2015. "Information sharing in contests." *Journal of Economics & Management Strategy*, 24(3): 570–596.

Krishna, Aradhna, Richard Briesch, Donald R. Lehmann, and Hong Yuan. 2002. "A meta-analysis of the impact of price presentation on perceived savings." *Journal of Retailing*, 78(2): 101–118.

Lazear, Edward P, and Sherwin Rosen. 1981. "Rank-order tournaments as optimum labor contracts." *Journal of Political Economy*, 89(5): 841–864.

Levin, Dan, and Emre Ozdenoren. 2004. "Auctions with uncertain numbers of bidders." *Journal of Economic Theory*, 118(2): 229–251.

Levin, Dan, and James L. Smith. 1994. "Equilibrium in auctions with entry." *American Economic Review*, 84(3): 585–599.

Lim, Wooyoung, Alexander Matros, and Theodore L Turocy. 2014. "Bounded rationality and group size in Tullock contests: Experimental evidence." *Journal of Economic Behavior & Organization*, 99: 155–167.

Lim, Wooyoung, and Alexander Matros. 2009. "Contests with a stochastic number of players." *Games and Economic Behavior*, 67(2): 584–597.

Liu, Tracy Xiao, Jiang Yang, Lada A Adamic, and Yan Chen. 2014. "Crowdsourcing with all-pay auctions: A field experiment on taskcn." *Management Science*, 60(8): 2020–2037.

Loomes, Graham, and Robert Sugden. 1982. "Regret theory: An alternative theory of rational choice under uncertainty." *The economic journal*, 92(368): 805–824.

Ludwig, Sandra, and Gabriele K Lünser. 2012. "Observing your competitor–The role of effort information in two-stage tournaments." *Journal of Economic Psychology*, 33(1): 166–182.

Lu, Jingfeng, Hongkun Ma, and Zhe Wang. 2017. "Ranking disclosure policies in all-pay auctions." *Economic Inquiry.*

Malmendier, Ulrike, and Geoffrey Tate. 2005. "CEO overconfidence and corporate investment." *The Journal of Finance*, 60(6): 2661–2700.

McAfee, R Preston. 1993. "Mechanism design by competing sellers." *Econometrica*, 1281–1312.

McAfee, R. Preston, and John McMillan. 1987. "Auctions with a stochastic number of bidders." *Journal of Economic Theory*, 43(1): 1–19.

McKelvey, Richard D., and Thomas R. Palfrey. 1995. "Quantal response equilibria for normal form games." *Games and Economic Behavior*, 10(1): 6–38.

Morgan, John, Dana Sisak, and Felix Várdy. 2018. "The ponds dilemma." *The Economic Journal*, 128(611): 1634–1682.

Morgan, John, Henrik Orzen, and Martin Sefton. 2012. "Endogenous entry in contests." *Economic Theory*, 51(2): 435–463.

Morgan, John, Henrik Orzen, Martin Sefton, and Dana Sisak. 2016. "Strategic and natural risk in entrepreneurship: An experimental study." *Journal of Economics & Management Strategy*, 25(2): 420–454.

Münster, Johannes. 2006. "Contests with an unknown number of contestants." *Public Choice*, 129(3-4): 353–368.

Myerson, Roger B, and Karl Wärneryd. 2006. "Population uncertainty in contests." *Economic Theory*, 27(2): 469–474.

Palfrey, Thomas R., and Svetlana Pevnitskaya. 2008. "Endogenous entry and self-selection in private value auctions: An experimental study." *Journal of Economic Behavior & Organization*, 66(3): 731–747.

Peters, Michael, and Sergei Severinov. 1997. "Competition among sellers who offer auctions instead of prices." *Journal of Economic Theory*, 75(1): 141–179.

Pevnitskaya, Svetlana. 2004. "Endogenous entry in first-price private value auctions: The self-selection effect." *Unpublished Manuscript.*

Rieck, Thomas. 2010. "Information disclosure in innovation contests." *Unpublished Manuscript.*

Roodman, David, Morten Ørregaard Nielsen, James G MacKinnon, and Matthew D Webb. 2019. "Fast and wild: Bootstrap inference in Stata using boottest." *The Stata Journal*, 19(1): 4–60.

Ryvkin, Dmitry, and Anastasia Semykina. 2017. "An experimental study of democracy breakdown, income and inequality." *Experimental Economics*, 20(2): 420–447.

Serena, Marco. 2015. "Harnessing beliefs to stimulate efforts." *Working paper*. http://dx.doi.org/10.2139/ssrn.2686543.

Shane, Scott, and Sankaran Venkataraman. 2000. "The promise of entrepreneurship as a field of research." *Academy of Management Review*, 25(1): 217–226.

Sheremeta, Roman M. 2010. "Experimental comparison of multi-stage and one-stage contests." *Games and Economic Behavior*, 68(2): 731–747.

Sheremeta, Roman M. 2013. "Overbidding and heterogeneous behavior in contest experiments." *Journal of Economic Surveys*, 27(3): 491–514.

Sutter, Matthias, Martin G. Kocher, Daniela Glätzle-Rützler, and Stefan T. Trautmann. 2013. "Impatience and uncertainty: Experimental decisions predict adolescents' field behavior." *American Economic Review*, 103(1): 510.

Tullock, Gordon. 1980. "Efficient rent seeking." *Toward a Theory of the Rent-Seeking Society*, , ed. James M. Buchanan, Robert D. Tollison and Gordon Tullock, 97–112. College Station:Texas A&M University Press.

Wolinsky, Asher. 1988. "Dynamic markets with competitive bidding." *Review of Economic Studies*, 55(1): 71–84.

Zhang, Jun, and Junjie Zhou. 2016. "Information disclosure in contests: A Bayesian persuasion approach." *Economic Journal*, 126(597): 2197–2217.

A Details of our QRE approach

Let B denote the discretized set of available investment levels 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

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

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

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

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

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

where

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

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

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

and the entry probability is

$$Q_d = \frac{\exp(\mu\pi_d)}{\exp(\mu\pi_d) + \exp(\mu\omega)}. \quad \text{(A.6)}$$

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 $\mu \to \infty$. For a finite μ, the payoffs also scale with ω. Therefore, for values of ω varying substantially across treatments, it is impossible to find a single value of μ fitting all the data. Indeed, suppose some value of μ fits the empirical entry probability Q_{nd} for $\omega = 6$. That same μ 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 μ. 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 $\hat{\mu} = \mu\omega$. With such renormalization, the equations for the equilibrium distributions of investments do not change except hats are added to all payoffs and μ. The equations for the equilibrium entry probabilities become

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

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 μ 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 $\hat{\mu}$. 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.[36] 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 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 $\hat{\mu}$ that best fits observed entry and investment behavior. We therefore compute the QRE over a grid of $\hat{\mu}$ points and select the value

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

which minimizes the sum of squared errors (SSE) given by

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

	Entry			Investment		
	Beliefs	Observed	Predicted	Beliefs	Observed	Predicted
D6	3.48	2.86	3.86	42.56	36.89	19.94
	[2.85 4.04]	[2.51 3.21]		[37.96 47.21]	[28.56 45.26]	
D48	3.19	1.87	1.16	46.20	44.60	20.50
	[2.84 3.53]	[1.57 2.19]		[37.85 54.62]	[33.27 55.36]	
ND6	3.22	2.38	3.86	43.59	45.06	19.94
	[2.81 3.64]	[2.09 2.66]		[32.39 54.27]	[37.32 54.11]	
ND48	2.87	1.80	1.16	33.07	28.23	20.50
	[2.67 3.06]	[1.52 2.07]		[25.34 40.91]	[22.99 33.26]	

Table B.1: Average beliefs by treatment, compared with observed averages (rounds 26-40) and predicted levels for entry and investment. 95% wild cluster bootstrap confidence intervals in brackets.

B Beliefs

Table B.1 reports 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 find that beliefs about entry are similar across treatments with the exception that beliefs in ND48 are lower than D6, D48 and ND6 (Wald tests: $p = 0.048$, $p = 0.084$ and $p = 0.095$, respectively). 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, there are no statistically significant differences). This may be driven by subjects attributing their own behavior to others and using their own investment as the response to the belief elicitation. Overall, beliefs exhibit limited consistency and provide no additional explanatory power for our analysis.

	Number of entrants						
Group id (ND6)	0	1	2	3	4	5	6
601	0	1	4	5	2	3	0
602	0	2	3	7	3	0	0
603	0	0	1	13	1	0	0
801	0	0	2	7	5	1	0
802	0	0	3	4	7	1	0
803	0	1	6	6	2	0	0
901	0	5	7	2	1	0	0
902	0	1	4	6	2	2	0
903	0	1	5	8	1	0	0

Table C.1: The distribution of the number of entrants by group (rounds 26-40).

C Do subjects play asymmetric equilibria?

The theoretical predictions in Section 3 focus on the unique symmetric SPNE, in which in stage 1 all players enter the contest with the same probability q^*, and in stage 2 all entrants either invest $x^*(q^*)$, Eq. (2), or invest $x^*_m = \frac{V(m-1)}{m^2}$, depending on disclosure. While the symmetric equilibrium is the most "natural" one to consider for symmetric players, this game also admits asymmetric equilibria in pure and mixed strategies. For example, let $\hat{m}$ denote the largest integer such that $\frac{V}{\hat{m}^2} \geq \omega$; then there is a pure strategy equilibrium where $\hat{m}$ players enter the contest with probability one, and the rest stay out. This equilibrium exists provided $2 \leq \hat{m} \leq n$ regardless of disclosure. For our parameters, $\hat{m} = 4$ when $\omega = 6$ and $\hat{m} = 1$ when $\omega = 48$; thus, there is a pure strategy equilibrium with 4 players entering in D6 and ND6. There may also be equilibria involving mixed strategies or a combination of pure and mixed strategies where players mix between entry and staying out with different probabilities.

Let us examine the possibility that subjects in our experiment play any of the asymmetric equilibria. In the D treatments, the equilibrium in the second-stage subgame is unique and symmetric, regardless of what players do in the first stage. The data clearly shows entrants' investment levels above the second-stage NE for every realized number of entrants in D6 and D48, cf. Figure 5 and Table 2. Thus, the data in the D treatments cannot support any asymmetric equilibrium with standard preferences.

In the ND treatments, in any equilibrium entrants should earn at least as much as non-entrants. This is clearly not the case in ND48, cf. Figure 4. The only remaining candidate for asymmetric equilibrium play is ND6 where the payoffs of entrants and non-entrants are roughly equalized. Table C.1 shows the distribution of the number of entrants (between 0 and 6) in the last 15 rounds of data for each group in ND6. In any group consistently playing an asymmetric equilibrium the number of entrants should be relatively stable. Let us focus on two groups: Group 603, where $m = 3$ with 13 observation is the clearly dominant number of entrants; and Group 903, where the realized number of entrants almost always takes two values, $m = 2$ and $m = 3$. The average investment in these two groups is 39.13 and 40.05, respectively, which is well above the NE investment for $m = 2$ (30) or $m = 3$ (26.67). Thus, there is no asymmetric equilibrium, pure or mixed, supporting this combination of entry and investment behavior.

It appears that due to the significant overbidding by entrants we can at least exclude asymmetric equilibria with standard incentives. However, we cannot exclude equilibria involving a combination of asymmetric entry with behavioral components, such as joy of winning, especially if we allow for different asymmetric equilibria to be played in different rounds. Identifying such equilibria in the data, due to their multiplicity, is impossible.

D Experimental instructions

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

Stage 1

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.[37]

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

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

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:

[37]The following sentence replaced the last sentence in 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."

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.[38]

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 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).

[38] 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."

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.[39]

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.[40] After the investment decisions are made by active group members, the program will determine the probability your project succeeds,

[39] 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."

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

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.