Journal of Economic Behavior and Organization 216 (2023) 243–267

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Asymmetric shocks in contests: Theory and experiment ☆

Jian Song [a,*], Daniel Houser [b]

[a] Economic Science Institute, Chapman University and Interdisciplinary Center for Economic Science, George Mason University, United States of America

[b] Department of Economics and Interdisciplinary Center for Economic Science, George Mason University, United States of America

ARTICLE INFO

JEL classification:
D90
M52
C90

Keywords:
Asymmetric random shock
Tournament
Laboratory experiment
Off-equilibrium behavior

ABSTRACT

Under optimal tournament design, equilibrium effort is invariant to the shape of the mean-zero additive stochastic component, often referred to as a “shock” or “noise”. We report data from laboratory experiments providing the first test of this prediction. Consistent with theory, we find that average effort does not significantly differ between a negatively skewed and uniform shock distribution. In addition, we test a second theoretical prediction that, in winner tournaments, when the shock distribution is asymmetric as in our design, one should exert minimum effort whenever one’s competitors are exerting above equilibrium effort. With a symmetric shock distribution as in our design, efforts should generally remain substantial, even when one’s competitors are exerting effort above equilibrium value. Our data reveal that subjects actively engage in the tournament even when faced with aggressive competitors under both shock distributions.

1. Introduction

Rank-order tournaments are ubiquitous in daily life. For instance, top students can earn top scholarships, and top-performing athletes can win gold medals. Due to tournaments’ importance, they have received a great deal of scholarly attention, much of it following from the seminal theory of Lazear and Rosen (1981). In this literature it is assumed that agents’ performance is determined by effort and a (typically additive) stochastic component referred to as the “shock” or the “noise”. The literature highlights that under optimal principal-agent contracts, the first best effort can be implemented with different shock distributions for risk neutral agents. There are many ways to implement the first best effort, including with different prize allocations. Therefore, it is somewhat surprising that the empirical/experimental literature informing this finding focuses on environments with symmetric shock distributions. As a result, it remains unknown the extent to which these implementations are empirically equivalent for different shock distributions.

As a practical matter, different shock distributions may be appropriate for different types of contests. For example, in “elite competitions” like the Olympics, scores typically cluster near the boundary of performance; however, there is a small chance that

☆ We thank the editor, the anonymous referees, Dmitry Ryvkin, Glenn Dutcher, Roman Sheremeta, Cesar Martinelli, Alexander Tabarrok, Johanna Mollerstrom, Marco Schwarz and participants at the ICES Brown Bag Lecture, APEE 44th International Conference, Contests: Theory and Evidence 5th Conference, 2019 North-American ESA Conference and SEA 89th Annual Meetings for helpful comments. This research was financed by the National Science Foundation (SES-2048519) and the Interdisciplinary Center for Economic Science (ICES) at George Mason University.

* Corresponding author at: Economic Science Institute, Chapman University, One University Drive, Orange, CA, 92866, United States of America.
E-mail addresses: jiansong@chapman.edu (J. Song), dhouser@gmu.edu (D. Houser).

https://doi.org/10.1016/j.jebo.2023.10.008
Received 15 December 2021; Received in revised form 27 September 2023; Accepted 8 October 2023

Available online 25 October 2023

an athlete will suffer an extremely negative shock (perhaps due to "choking"[1]). Symmetric shock distributions cannot capture this phenomenon.

The shock distribution also plays an important role in tournaments where the goal is simply not to lose. For example, in the final round of the Olympic 25 m Rapid Fire Pistol competition, six athletes can shoot up to eight five-shot series for the gold medal. However, after the fourth series, the athlete with the lowest aggregate score is eliminated from the final and places sixth. Elimination of the lowest-scoring performer continues until the Gold and Silver medalists are decided at the eighth series. Once again, most scores are clustered near the boundary. The few low scores can be understood as very negative shock realizations. Given how important asymmetric shock distributions are to multiple tournament structures, it is worth developing a deeper understanding of behavior in these environments. Our paper takes on this challenge.

Using the seminal theory framework of Lazear and Rosen (1981) and building from the experimental analysis of Dutcher et al. (2015), we investigate rank-order tournaments within the setting of optimal principal-agent contracts.[2] Under optimal contracts, both prize and tournament structures are related to the shape of the shock distributions. The efficient level of effort, however, is invariant to the distribution's shape. We test whether this prediction holds empirically.

We conducted experiments with treatments that differed in both the shock distribution and the tournament structure. We used shock processes that followed either a uniform or beta distribution to capture symmetric and asymmetric distributions, respectively.[3] Following Dutcher et al. (2015), we consider two tournament structures: The first is the winner tournament, where subjects strive to finish in first place. A top prize is awarded to the subject with the highest output, while the remaining subjects receive an identical but smaller prize. The second is the loser tournament, where subjects strive to avoid finishing in last place. The subject with the lowest output receives a bottom prize, while the remaining subjects earn an identical but larger prize. Comparing effort under different treatments within optimal principal-agent contracts, we investigate how subject behavior is influenced by the nature of a tournament.

To explicitly investigate the impact of previous shock realizations on current effort provision, the groups in our experiment were randomly re-matched in every round. At the end of each round, subjects were only informed of the values of the random shocks, as well as whether they won or lost the contest. They did not receive any information about their group members' effort. Using these methods, we minimize the impact of group members' decisions on one's own effort decision.[4]

Further, we compare individual behavior under different distributions of random shocks. Individual effort decisions have been heavily investigated in the literature. A common finding is that there is heterogeneity in effort provision among tournament participants (see Dechenaux et al. (2015)). When individuals face the possibility of highly negative shocks, the impact on individual heterogeneity becomes uncertain. For example, high-effort contestants may increase their effort to compensate for the effects of extremely negative shocks and improve their chances of winning, thereby amplifying heterogeneity. On the other hand, in asymmetric shock environments the influence of effort on tournament outcomes may diminish, potentially leading high-effort contestants to become discouraged and reduce their efforts, consequently reducing heterogeneity. Our study investigates the effects of asymmetric shocks, particularly distributions with negative skewness, on effort heterogeneity.

We observe that although there is no statistically significant difference in the average effort provision of tournament participants between the environments with symmetric and asymmetric shocks, their responses to their group members' off-equilibrium behavior are not consistent with theoretical predictions. In winner tournaments, where participants have the chance to encounter extremely negative shocks in the asymmetric shock treatment, the prize for not winning the tournament should be larger compared to the symmetric shock treatment to compensate for extremely bad luck. Consequently, even if participants exert extremely low effort, their expected payoff can remain relatively high. As a result, in the asymmetric shock treatment, when participants' group members exert above equilibrium effort, the optimal response for tournament participants is to avoid competition by exerting extremely low effort.[5] Conversely, in winner tournaments with symmetrically distributed shocks, if participants' group members overbid, the best response for the tournament participants is to exert high effort as well. Our data demonstrate a deviation from these theoretical predictions. When group members exhibit aggressive behavior, participants in both the symmetric and asymmetric shock treatments react aggressively. This indicates that in winner tournaments, participants in the asymmetric shock treatment fail to respond effectively to their group members' overbidding.

In contrast, in loser tournaments, where the objective shifts to "punishing the worst", the bottom prize in a loser tournament is typically lower than the prize for not winning in a winner tournament under the same shock distribution. This reduced bottom prize in loser tournaments diminishes participants' incentive to exert extremely low effort. Specifically, when participants' group members display aggressive behavior in loser tournaments, the optimal response to avoid finishing last and receiving the lowest prize is to

[1] See Hill et al. (2010) for the literature review on choking in sports contests.

[2] Optimal principal-agent contracts are characterized by: (1) Agents choose efforts that maximize their expected payoffs; (2) The principal operates in a competitive labor market under zero-profit condition; (3) The principal chooses the prize structure to maximize agents' expected payoffs.

[3] Subjects were provided detailed instructions, sample draw sequences and histograms to help them understand the beta distribution. They also answered a quiz to ensure they understood the distribution.

[4] There are some studies that investigate the impact of strategic momentum on subjects' behavior (e.g. Mago et al. (2013); Mago and Sheremeta (2019)). However, to establish the strategic momentum, subjects are grouped with the fixed members, which is opposite to our experimental design. Moreover, as stated in Dutcher et al. (2015), random re-matching is implemented to "reduce reputation effects and mimic the one-shot setting as closely as possible".

[5] It is important to note that a drop-off in the best response can occur in treatments where the shock follows a symmetric distribution (e.g., the WIN6 treatment in Dutcher et al. (2015)). This phenomenon occurs due to the influence of multiple factors on individuals' best response function. These factors include elements such as the tournament structure, shock distribution, and tournament size, among others. In our investigation, we specifically concentrate on evaluating the effects of shock distribution and tournament structure, while maintaining a fixed tournament size.

exert high effort, regardless of whether the shock distribution is symmetric or asymmetric. Consistent with theoretical predictions, our empirical data demonstrates that when group members exert excessively high effort in loser tournaments, participants respond aggressively in both symmetric and asymmetric shock environments. Furthermore, there is no statistically significant difference in participants' response to their group members' overbidding behavior between the symmetric and asymmetric shock treatments.

Our findings underscore the significance of considering the dynamics of various tournament types and shock distributions in shaping participants' responses and strategic choices within competitive settings. Specifically, the difference in contestants' responses to their opponents' off-equilibrium behavior, particularly in winner tournaments, highlights the importance of examining individual behavior exclusively in asymmetric shock environments. In particular, our results demonstrate that contestants exhibit a higher level of aggression than what was predicted by theory in the negative-skewed shock environment, given that they hold the beliefs that their opponents are aggressive. The deviations observed in our study benefit the contest designer and the contest audience, as contestants are not deterred by their aggressive opponents and the possibility of extremely negative shocks. Consequently, the expected total effort, given that opponents engage in overbidding, is actually greater than theory predicts.

This paper proceeds as follows: Section 2 provides a brief literature review. Section 3 describes the model. Section 4 details the experiment design and predictions. Section 5 reports the results. Section 6 offers concluding remarks.

2. Literature review

Following Lazear and Rosen (1981), the contest literature extensively explored the theoretical foundation of rank-order tournaments (Green and Stokey (1983); Bhattacharya (1985); McLaughlin (1988); Lazear (1999)). Bull et al. (1987) was the first experimental study to investigate subjects' behavior in rank-order tournaments.

The literature has extensively investigated how optimal prize structures vary with shock distributions: Gerchak and He (2003) contradicted the common wisdom by pointing out that under certain shock distributions, the optimal prize spreads do not decrease with the variance of distributions. Akerlof and Holden (2012) and Hartig and Reitzner (2017) both provided theoretical investigations of rank-order tournaments under various shock distributions. While Akerlof and Holden (2012) focused on how shock distribution affects the magnitude of prize structures, Hartig and Reitzner (2017) analyzed how shock distribution affects the optimal number of winners in rank-number tournaments. Drugov and Ryvkin (2020) specifically investigated how the presence of heavy tails in the distribution of shocks affects the optimal allocation of prizes in rank-order tournaments. By contrast, our study investigates rank-order tournaments under optimal contracts. In this environment, effort should be invariant to the shape of the shock distribution.

To the best of our knowledge, List et al. (2020) is the only experimental study that examines how distribution of random shocks impacts rank-order tournaments. They reported that if there is considerable (little) mass on good draws, equilibrium effort is an increasing (decreasing) function of the number of contestants. In our study, we hold the number of contestants as fixed, allowing us to focus exclusively on the effect of the shape of the shock distribution on effort.

Most research on contests focuses on reward structures. Optimal punishment was first studied by Mirrlees (1999). In recent years, significant research has compared the two types of contests. For example, Moldovanu et al. (2012) found that even when punishment is costly, greater effort can be elicited by punishing the bottom participant, rather than rewarding the top participant. By contrast, Thomas and Wang (2013) studied an all-pay contest with endogenous entry. They noted that if a contest designer wishes to maximize the total effort from all potential players, the optimal punishment should be zero for a wide class of cases. Recent work by Fang et al. (2020) demonstrated that in the all-pay contests where contestants are homogeneous and have convex effort costs, increasing contest competitiveness by making prizes more unequal, always discourages effort. Dutcher et al. (2015) conducted a laboratory experiment to compare effort exertion under the optimal principal-agent contracts with different tournament structures. They found that loser tournaments produce the lowest variance in effort and are more effective than winner tournaments at motivating employees.

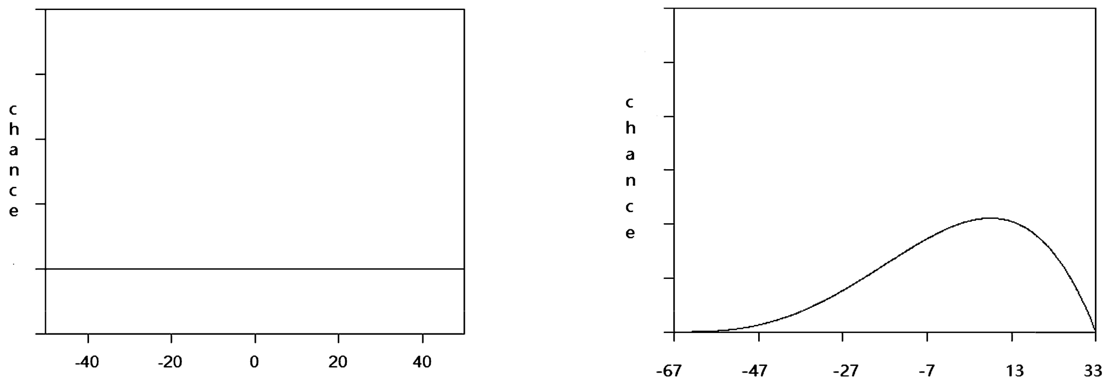
Regarding the literature on how individuals behave in rank-order tournaments, one major finding is that although there is little to no overbidding in rank-order tournaments on average, heterogeneity of individual behavior is widespread (Dechenaux et al. (2015)). Drago and Heywood (1989) argued that some of the variance in effort exertion can be attributed to relatively flat payoff functions. Eriksson et al. (2009) found that allowing subjects to choose their payment scheme (tournament or piece-rate scheme) can significantly reduce the variance in effort exertion. Gill et al. (2018) provided an alternative explanation, arguing that ranking significantly affects exertion, as subjects work their hardest after being ranked first or last, which increases the variance in effort.

3. The model

We model an environment with optimal principal-agent contracts, as in Lazear and Rosen (1981) and Dutcher et al. (2015). There are $n \geq 2$ identical risk-neutral subjects.[6] Each subject participates in the tournaments by exerting effort $e_i \geq 0$. The cost of effort e_i to subject i is $c(e_i)$, where $c(\cdot)$ is the cost function. The cost function is the same for all subjects and is strictly increasing and strictly convex. Subject i's output is $y_i = e_i + \varepsilon_i$, where ε_i is a zero-mean idiosyncratic random shock. We assume that ε_i are i.i.d. drawn from distribution with pdf $f(\varepsilon)$ and cdf $F(\varepsilon)$.

In rank-order tournaments, subjects are evaluated on the basis of their relative performance. For the winner tournament, let w_1 be the prize for the subject whose output is greatest, and w_2 be the prize for the remaining subjects, where $w_1 > w_2$. For the loser tournament, let v_2 be the prize for the subject whose output is least, and let v_1 be the prize for the remaining subjects, where $v_1 > v_2$.

[6] We restricted our attention to the symmetric Nash equilibrium. There may be other equilibria that are not symmetric.



(a) probability density function of ε_1 (b) probability density function of ε_2

Fig. 1. Probability density function of (a) ε_1 and (b) ε_2.

According to Lazear and Rosen (1981), Akerlof and Holden (2012) and Dutcher et al. (2015), we derive that, under the optimal principal-agent contracts, $c'(e^*) = c'(\bar{e}) = 1$, where e^* and $\bar{e}$ represent the equilibrium effort in the winner tournament and the loser tournament respectively. Given that the cost function is strictly convex, we obtain $e^* = \bar{e}$. This means that under the optimal principal-agent contracts, in equilibrium, subjects exert the same level of effort in the winner and loser tournaments. We can also reveal the following optimal prize structures:

$$w_1 = e^* + \frac{n-1}{n\beta_1} \qquad w_2 = e^* - \frac{1}{n\beta_1} \tag{1}$$

$$v_1 = \bar{e} + \frac{1}{n\left|\beta_n\right|} \qquad v_2 = \bar{e} - \frac{n-1}{n\left|\beta_n\right|} \tag{2}$$

Where $\beta_1 = (n-1)\int F(x)^{n-2} f(x)^2 dx$ and $\beta_n = -(n-1)\int (1-F(x))^{n-2} f(x)^2 dx$. The detailed derivations can be found in Appendix A.

Based on our analysis, we observe that while equilibrium effort is identical between the winner and loser tournaments, the coefficients β_1 and β_n are contingent on the noise distribution. Consequently, the optimal prize structures are influenced by the noise distribution. Existing studies, such as those conducted by Shupp et al. (2013) and Cason et al. (2020), have shown deviations from the standard model's predictions are related to variations in prize allocations. Therefore, the noise distribution could plausibly be expected to have an effect on effort.[7]

4. Experimental design and hypotheses

4.1. Parameters of experiments

4.1.1. Parameters of random shocks

Our experiments use two different distributions of random shocks. The first, which represents symmetric random shocks, is a uniform distribution. Due to its simplicity, the uniform distribution is widely used in experimental studies on rank-order tournaments. In our experiment, the uniform random shock is modeled as:

$$\varepsilon_1 = 100 \times [\gamma_1 - E(\gamma_1)] \tag{3}$$

where $\gamma_1 \sim U(0,1)$.

We use the beta distribution $Beta(\alpha, \beta)$ to represent the asymmetric random shocks. The reason we use this kind of distribution is that when $\alpha > \beta > 1$, it becomes unimodal and negatively skewed. This means that the probability of drawing a number that is far lower than the mean is higher than the probability of drawing a number that is far higher than the mean. This distribution can help depict competitions like an "elite competition" more accurately. For simplicity, in our experiment, the asymmetric shock is modeled as:

$$\varepsilon_2 = 100 \times [\gamma_2 - E(\gamma_2)] \tag{4}$$

where $\gamma_2 \sim Beta(4,2)$. Fig. 1 depicts the probability density function (pdf) of ε_1 and ε_2.

4.1.2. Parameters of cost function

For the cost function of effort, we use $c(e) = c * [\left(A - \frac{e}{100}\right)^{-r} - A^{-r}]$, with $c > 0,\ A > 0,\ r > 0$. From (A.13), we can derive the optimal effort level as:

[7] We thank an anonymous referee for suggesting this point.

Table 1
Treatments and parameters of experiments. Note: QRE indicates the expected effort of the quantal response equilibrium with the noise parameter $\lambda = 20$. The values of prizes are measured in token (experimental currency).

Treatment	n	c	A	r	Prizes		e*	π	QRE
aymm_winner	3	482.3	1.1	1.3	$w_1 = 11850$	$w_2 = 6075$	80	6120	63.91
symm_winner	3	482.3	1.1	1.3	$w_1 = 14667$	$w_2 = 4667$	80	6120	71.27
asym_loser	3	482.3	1.1	1.3	$v_1 = 10310$	$v_2 = 3380$	80	6120	74.86
symm_loser	3	482.3	1.1	1.3	$v_1 = 11330$	$v_2 = 1330$	80	6120	75.26

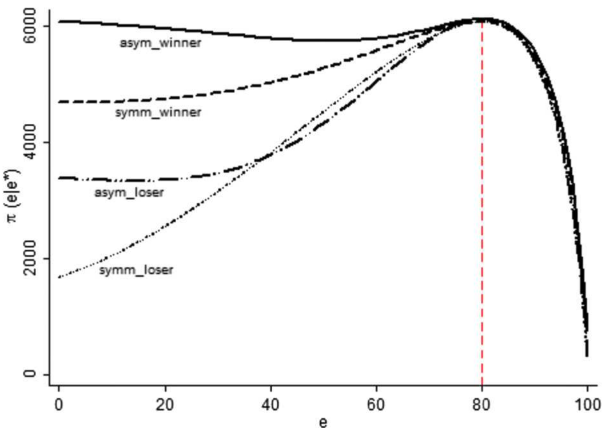


Fig. 2. Expected payoffs of subject's efforts, $\pi(e|e^*)$.

$$e^* = \bar{e} = 100 * [A - (rc)^{\frac{1}{r+1}}] \tag{5}$$

Next, we find the cost parameters that can generate a symmetric pure strategy Nash equilibrium in all treatments. The parameters in all treatments are summarized in Table 1.[8]

4.2. Theoretical predictions

4.2.1. Pure-strategy Nash equilibrium

To verify that choosing 80 is the pure strategy Nash equilibrium in all treatments under the parameters mentioned in Table 1, we calculate the expected payoff for each subject, $\pi(e|e^*)$, where the payoff is the function of subject's effort exertion, e, given that all other group members choose the equilibrium effort, e^*. Fig. 2 shows the values of $\pi(e|e^*)$ under different levels of e, which confirms that $e^* = 80$ is the pure strategy Nash equilibrium.[9]

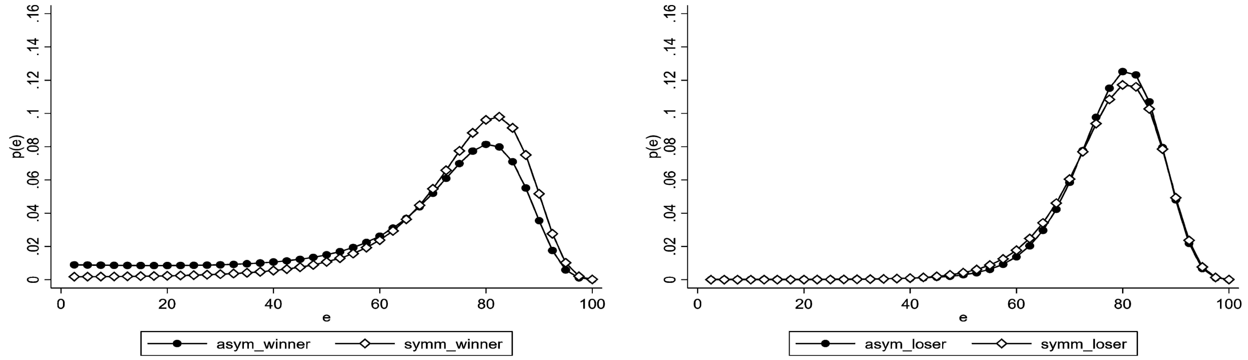
4.2.2. Quantal response equilibrium

As noted by Dutcher et al. (2015), due to the relative flatness of the payoff functions and the corresponding possibility that subjects will deviate from Nash strategies, it is sensible to consider quantal response equilibria (QRE) (McKelvey and Palfrey (1995)) in this environment. Fig. 3 shows the QRE distributions of effort using the noise parameter $\lambda = 20$[10] in winner and loser tournaments. Intuitively, if subjects face a flatter payoff function, they would receive less "punishment" if they deviate and are more likely to lower their effort provisions. Therefore, subjects have higher chance to exert low effort in *asym_winner* compared with in *symm_winner*. The incentives subjects face in loser tournaments is more complex; subjects in *asym_loser* are more likely to exert effort in the lower range, less likely to exert effort in the intermediate range, and more likely to exert effort in the higher range compared with those in *symm_loser*. The expected QRE efforts, in the winner tournaments, are ranked as: 63.91 in *asym_winner* and 71.27 in *symm_winner*; in the loser tournaments, they are ranked as: 74.86 in *symm_loser* and 75.26 *asym_loser*.

8 In our treatments, we use *"asym"* and *"symm"* to represent whether the shock distributions are asymmetric or symmetric; we use *"winner"* and *"loser"* to represent whether the tournaments are winner tournaments or loser tournaments. More details are provided in Section 4.4.

9 In the *asym_winner*, $\pi(80|e^*) = 6120$ and $\pi(0|e^*) = 6075$, choosing the effort of 80 generates the global maximum payoff.

10 We calculate the expected QRE effort under different values of noise parameter, λ. We find that among those noise parameters, $\lambda = 20$ fits our data best. See Appendix D for detailed analysis.



(a) winner tournaments (b) loser tournaments

Fig. 3. QRE distributions of efforts in (a) winner tournaments and (b) loser tournaments.

4.3. Hypotheses

Our experiment investigates how shock distributions and tournament structures affect effort. Although the pure-strategy Nash equilibrium predicts no difference in effort exertions across all treatments, from the results of previous experimental studies, we believe that subjects will deviate from pure-strategy Nash equilibrium predictions. To capture such deviations, we use the QRE expected efforts as prediction benchmarks. We calculate the average effort in asymmetric and symmetric shock treatments, and obtain the following two hypotheses:

Hypothesis 1. The average effort exertion in the asym_winner treatment is less than in the symm_winner treatment.

Hypothesis 2. The average effort exertion in the asym_loser treatment is no less than in the symm_loser treatment.

4.4. Experimental design

We employ a 2×2 design to test the above hypothesis. There are two different distributions of random shocks: symmetric (uniform) distribution and asymmetric (beta) distribution. Likewise, there are two different tournament structures: the winner tournament, in which the subject with highest total output received the top prize w_1 and others received an identical but smaller prize w_2; and the loser tournament, in which the subject with lowest total output received the bottom prize v_2 and others received an identical but greater prize v_1. We refer to our treatments as *symm_winner*, *symm_loser*, *asym_winner* and *asym_loser* respectively.

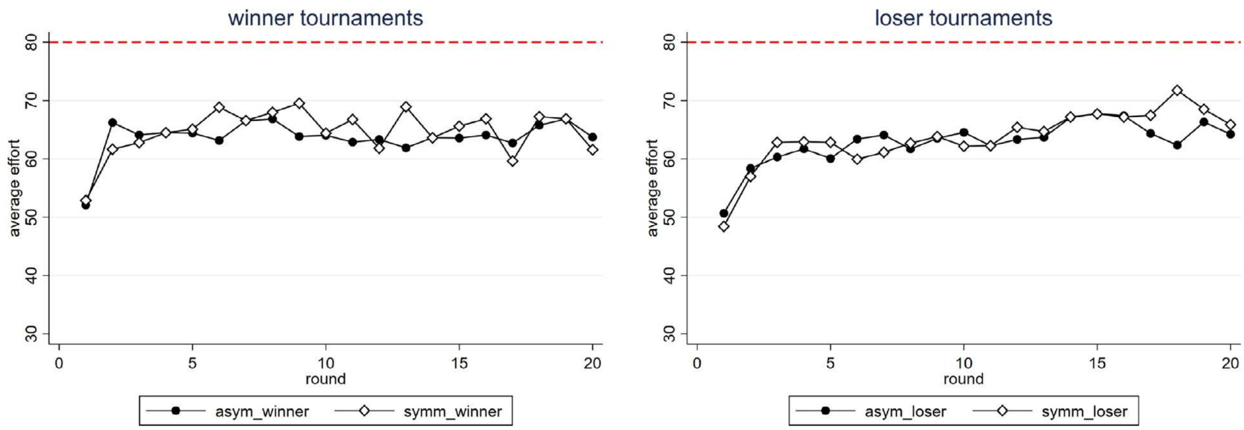
Before the experiment began, subjects were given instructions[11] for the first part of the experiment. The instructions were also read aloud by the experimenter. After subjects finished reading the instructions and completed the comprehensive quiz successfully, they were given examples[12] to help them gain a better understanding of the characteristics of random shocks mentioned in the instructions. They then proceeded to an effort choice game, which was the most important part of our experiment.

The effort choice game consisted of 20 rounds. Subjects competed in groups of three. In each round, subjects were randomly and anonymously matched in a group with other participants in the session. To keep the terminology neutral, in the instructions we described the effort as "number" and subjects were asked to choose a whole number between 1 and 100. After all the group members made their choices, random numbers were generated by the computer in the asymmetric (symmetric) treatments. These numbers followed an asymmetric (symmetric) distribution, and the distribution was fixed within a session. All random numbers were independently drawn for each subject in every round of the experiment. Subject's total number was the sum of the number they chose, plus the random number chosen by the computer. By comparing the total numbers in each group, we were able to determine the rank for each subject. In *symm_winner* and *asym_winner*, the subject with the highest total number in each group won the top prize w_1 tokens, while the others won a lower prize w_2 tokens. In *symm_loser* and *asym_loser*, the subject with the lowest total number in each group received the bottom prize v_2 tokens, while the others received a higher prize v_1 tokens. All 20 rounds followed the same procedure mentioned above. As in Dutcher et al. (2015), after the last round, we elicited, in an incentivized manner, subjects' beliefs about each of the other group members' effort choices in that round. At the end of the experiment, four rounds were selected randomly and subject were paid based on the results of these four rounds with an exchange rate of 2000 tokens to 1 US dollar.

After all subjects completed the effort choice game, they were asked to complete a short demographic questionnaire, followed by an incentivized risk-aversion task (Holt and Laury (2002)) and an incentivized loss-aversion task (Gächter et al. (2007)). When all subjects finished these parts, they were paid in cash privately.

[11] Sample instructions for *asym_winner* are provided in Appendix B, the instructions for all other treatments, are provided in the supplementary materials.

[12] Sample examples for the asymmetric shock distribution are provided in Appendix C, other examples are provided in the supplementary materials.



(a) winner tournaments (b) loser tournaments

Fig. 4. Average efforts in (a) winner tournaments and (b) loser tournaments. The red dashed line represents the Nash equilibrium prediction. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

The experiments were programmed in z-Tree (Fischbacher (2007)). We conducted all experiments at George Mason University. The first phase of data collection lasted from June 2018 to October 2018, and the second phase of data collection occurred in November 2022.[13] A total of 336 students participated in our experiments (90 subjects in *asym_winner*; 78 subjects in *symm_winner*; 87 subjects in *asym_loser*; 81 subjects in *symm_loser*). We conducted 28 sessions with seven sessions in each treatment. The experiments lasted for about an hour and a half. Subjects earned $21.64 in the first phase and $22.95 in the second phase (including show-up fees[14]), on average.

5. Results

5.1. Average efforts

The average efforts exerted by subjects in the four treatments are shown in Fig. 4. On average, subjects in *asym_winner* exerted effort of 63.70; subjects in *symm_winner* exerted effort of 64.65; subjects in *asym_loser* exerted effort of 62.85; and subjects in *symm_loser* exerted effort of 63.58. Within treatments, subjects (weakly) underbid in relation to the QRE equilibrium predictions (Wald test based on Column (2) of Table 2; $p = 0.962$ for the comparison between *asym_winner* effort and the QRE prediction; $p = 0.078$ for the comparison between *symm_winner* effort and the QRE prediction; $p < 0.001$ for the other two treatment comparisons). On the aggregate level, the QRE model performs better than the Nash equilibrium model in predicting subjects' behavior in winner tournaments, while neither the QRE model nor the Nash equilibrium model accurately predicts subjects' behavior in loser tournaments.

Comparing effort provision between treatments, we see little difference for the average effort provision between *asym_winner* and *symm_winner* (Wald test based on Column (2) of Table 2, $p = 0.401$), nor between *asym_loser* and *symm_loser* (Wald test based on Column (2) of Table 2, $p = 0.803$).[15] Therefore, we reject Hypothesis 1, while failing to reject Hypothesis 2. Our first and second results are as follows.

Result 1. Unlike the ordinal relation in QRE predictions, we find no statistically significant differences in effort exertion between the asym_winner and symm_winner treatments.

Result 2. Consistent with the ordinal relation in QRE predictions, we find no statistically significant differences in effort exertion between the asym_loser and symm _loser treatments.

Fig. 5 displays the histograms depicting the distribution of effort exertion across different treatments.[16] Our analysis reveals a considerable variance in individual behavior. In winner tournaments, we observe the presence of the "bifurcation" phenomenon, previously reported by Dutcher et al. (2015), wherein many subjects exerted efforts within the ranges of 1-10 and 91-100. However,

[13] Each subject was only allowed to participate in our experiment once. We calculate the gender ratio and average risk/loss preference between these two phases. The summary statistics of subjects' traits are shown in Tables E.1 and E.2; The summary statistics of random shocks drawn by treatment are shown in Tables E.3 and E.4 of Appendix E.

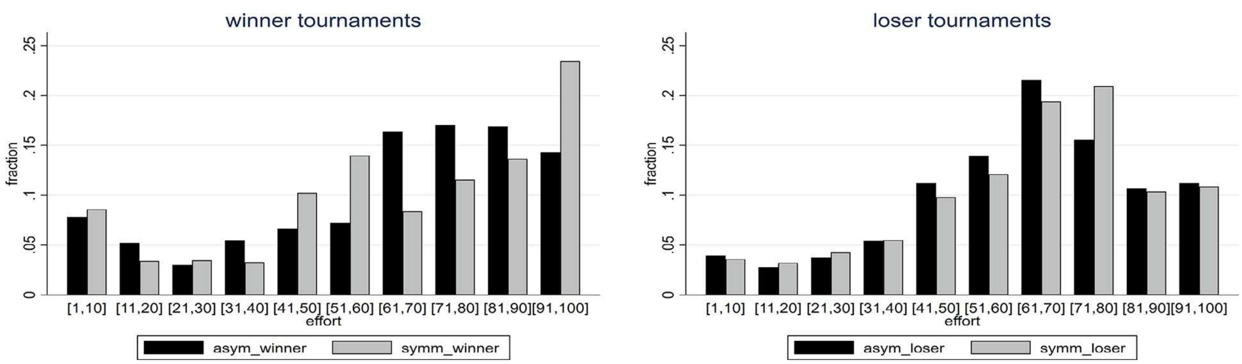
[14] The show-up fees was $5 for the first phase and was $7 for the second phase.

[15] Qualitatively, our results are consistent with the Nash equilibrium model.

[16] As in Dutcher et al. (2015), a non-negligible fraction of subjects choose maximum effort, which is of course above its equilibrium value. Possible reasons for this overbidding include bounded rationality, positive utility of winning (Sheremeta (2010)), other-regarding preferences (Mago et al. (2016), Song and Houser (2021)), probability distortion or the shape of the payoff function. Sheremeta (2013) provides an excellent discussion of this issue.

Table 2
OLS regressions with standard errors clustered at the session level and adjusted for the small number of clusters using the Bias-Reducing Linearization procedure (BRL) of Bell and McCaffrey (2002). The dependent variable is the effort exerted by subjects. Independent variables include treatment dummies and use the asym_winner treatment as the reference group. Column (2) controls for gender, round, and a subject's degree of risk seeking and loss aversion levels. Risk seeking indicates the number of risky choices subjects made in the risk aversion task; Loss aversion indicates the number of lotteries subjects refused to play in the loss aversion task. *, **, *** denotes statistical significance at the 10%, 5%, 1% level.

	(1)	(2)
Symm_winner	0.950	0.899
	(3.942)	(2.333)
Asym_loser	−0.850	−1.134
	(3.754)	(3.956)
Symm_loser	−0.119	0.153
	(1.852)	(4.441)
Loss aversion		−0.207
		(0.431)
Risk seeking		−0.158
		(0.583)
Male		3.726***
		(1.111)
Round		0.354
		(0.253)
Constant	63.702***	59.328***
	(3.731)	(4.557)
Observations	6720	6720
Clusters	28	28



(a) winner tournaments (b) loser tournaments

Fig. 5. Histogram of effort provision in (a) winner tournaments and (b) loser tournaments.

contrary to the expectations based on the QRE prediction presented in Fig. 3, subjects in the *asym_winner* treatment did not show a greater inclination to exert effort below 10. On the other hand, subjects in the *symm_winner* treatment demonstrated a higher likelihood of exerting effort above 90, which aligns with the QRE prediction. Moving on to the analysis of loser tournaments, we noted a less pronounced "bifurcation" phenomenon, with the majority of subjects exerting effort between 61-80. Additionally, we found no statistically significant difference in the fraction of effort within the range of 61-80 between the *asym_loser* and *symm_loser* treatments. For detailed results of the statistical tests conducted, please refer to Table E.5.

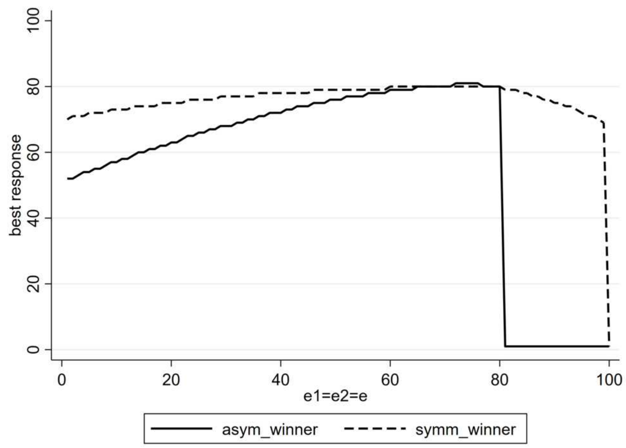


Fig. 6. Best response calculation. Note: the calculation is based on the assumption that both group members exert identical effort $e_1 = e_2 = e$.

5.2. Individual efforts

5.2.1. Individual efforts in winner tournaments

Based on the analysis presented in Fig. 5, it is evident that the QRE prediction fails to capture the qualitative relationship between the effort exertion in the *asym_winner* and *symm_winner* treatments because subjects in the *asym_winner* treatment did not demonstrate a higher likelihood to exert extremely low effort. To study this further, Fig. 6 provides subjects' best response effort given the group members' effort equals $e_1 = e_2 = e$.

In Fig. 6 a notable distinction emerges between the *asym_winner* and *symm_winner* treatments in terms of how subjects should respond to their group members' overbidding. In *asym_winner*, when group members exert effort above the Nash equilibrium value of 80, the optimal strategy for subjects is to choose the minimum level of effort, which in our case is 1.[17] Conversely, in the *symm_winner* treatment, despite overbidding by group members, the optimal response for subjects is to continue actively participating in the tournaments, albeit with a slightly reduced level of effort compared to the Nash equilibrium prediction.[18]

In order to examine empirically whether subjects effectively best respond to their group members' overbidding, we narrow our focus to a specific subgroup of observations where both of their group members' efforts exceed 80. This subgroup comprises a total of 401 observations, with 177 belonging to the *asym_winner* treatment and 224 to the *symm_winner* treatment. Upon analyzing these observations, we find that, on average, subjects in the *asym_winner* treatment chose an effort level of 65.27, while those in the *symm_winner* treatment exerted an effort level of 65.91. Notably, there is no statistically significant difference in the average effort provision between the two treatments (Wald test based on Column (1) of Table 3, $p = 0.981$). This finding suggests that subjects in both treatments exhibit a similar level of effort provision in response to their group members' overbidding, regardless of the shock distribution.

Furthermore, we calculate the absolute difference between subjects' actual effort and their best responses, given both of their group members' efforts are over 80. The average absolute difference, aggregated by treatment and round, is presented in Fig. 7.

We observe that, in response to their group members' overbidding behavior, subjects in the *asym_winner* treatment exhibited a poorer performance in terms of best response compared to those in the *symm_winner*.[19]Moreover, as the rounds progressed (after round 5), the discrepancy between these two treatments becomes more pronounced. As the session advanced, effort choices did not converge towards best response. To explore this further we conducted a regression analysis, the results of which are presented in Column (1) of Table 4. The regression analysis provides additional support for the aforementioned observations.

One potential explanation for the failure of subjects in the *asym_winner* treatment to best respond to their group members' overbidding behavior is incorrect beliefs.[20] To investigate this hypothesis, we employ the last round's subjects' guesses regarding

[17] As depicted in Fig. 2, it is evident that as effort varies from 1 to 100, the payoff function for the *asym_winner* treatment achieves a local maximum at the effort level of 1 ($\pi(1|e^*) = 6070$), which is very close to the global maximum at 80 ($\pi(80|e^*) = 6120$). Consequently, small departures from Nash equilibrium play, where both group members overbid, leads effort at 1 becoming the global maximum. The result is that the best response switches discontinuously to 1 in the presence of overbidding. There are no similar effects for other treatments.

[18] In the *symm_winner* treatment, the best response for subjects is to choose 1 only when $e_1 = e_2 = 100$. In all other cases, the optimal response are greater than 65.

[19] However, upon examining the payment earned by subjects in the *asym_winner* and *symm_winner* treatments when their group members' efforts exceeded 80, it was observed that, on average, subjects in the *asym_winner* treatment earned 4840.41 tokens, while those in the *symm_winner* treatment earned 3954.44 tokens. Notably, subjects in the *asym_winner* treatment earned significantly higher compared to those in the *symm_winner* treatment (Wald test based on an OLS regression with standard errors clustered at the session level and using the BRL adjustment, independent variables are the treatment dummy, the time trend, the gender of the subject, as well as their risk and loss preferences, $p < 0.01$). Despite this difference, it is important to highlight that subjects in the *asym_winner* treatment earned significantly less than the predicted optimal payoff they could have attained (Wald test based on an OLS regression with standard errors clustered at the session level and using the BRL adjustment, independent variables are the treatment dummy, the time trend, the gender of the subject, as well as their risk and loss preferences, $p < 0.01$).

[20] Given that subjects did not receive information on their group members' effort at the end of each round, it is not meaningful for us to assess whether subjects were myopically best responding to their group members' efforts in the previous round.

Table 3
OLS regressions with standard errors clustered at the session level and adjusted for the small number of clusters using the Bias-Reducing Linearization procedure (BRL) of Bell and McCaffrey (2002). The dependent variable is the effort exerted by subjects in (1) winner tournaments and (2) loser tournaments, given their group members' efforts exceed 80. The independent variables in the model include a treatment dummy, with the asymmetric shock treatment serving as the reference group. Additionally, we controlled for the time trend, the gender of the subjects, and their levels of risk-seeking and loss aversion. Risk seeking indicates the number of risky choices subjects made in the risk aversion task; Loss aversion indicates the number of lotteries subjects refused to play in the loss aversion task. The loser tournaments only have 13 clusters as there is no observations where both group members' efforts exceed 80 in one session collected during phase 1 of the *symm_loser* treatment. *, **, *** denotes statistical significance at the 10%, 5%, 1% level.

	(1) winner tournaments	(2) loser tournaments
Asym	-0.561	-7.626*
	(24.052)	(4.209)
Loss aversion	-0.951	-1.993
	(1.088)	(1.438)
Risk seeking	-0.688	-0.836
	(2.076)	(2.120)
Male	7.385	-0.115
	(31.066)	(4.589)
Round	-0.027	0.872**
	(0.840)	(0.397)
Constant	68.372***	64.568***
	(1.522)	(8.535)
Observations	401	146
Clusters	14	13

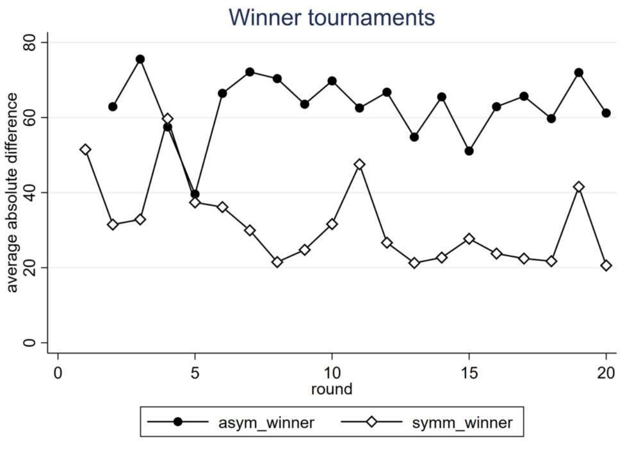


Fig. 7. The average absolute difference between the subject's effort and the best response, given that both of their group members' efforts are above 80, by treatment and round. Note: the *asym_winner* treatment only has 19 observations, the reason is because there were no such observations in round 1 where both group members' efforts were above 80.

their group members' efforts and examine whether subjects respond by exerting excessively low effort when they believe both of their group members' efforts will exceed 80. Out of the 90 subjects in the *asym_winner* treatment, 14 of them held the belief that both of their group members would exert effort above 80. Surprisingly, only 2 out of these 14 observations responded by exerting effort below 20, while the remaining 12 subjects exerted effort above 65. This finding demonstrates that even when subjects hold the

Table 4
OLS regressions with standard errors clustered at the session level and adjusted for the small number of clusters using the Bias-Reducing Linearization procedure (BRL) of Bell and McCaffrey (2002). The dependent variable is the absolute difference between the effort exerted by subjects and the corresponding best response in (1) winner tournaments and (2) loser tournaments, given their group members' efforts exceed 80. The independent variables in the model include a treatment dummy, with the asymmetric shock treatment serving as the reference group. Additionally, we controlled for the time trend, the interaction between the time trend and the treatment dummy, the gender of the subjects, and their levels of risk-seeking and loss aversion. Risk seeking indicates the number of risky choices subjects made in the risk aversion task; Loss aversion indicates the number of lotteries subjects refused to play in the loss aversion task. The loser tournaments only have 13 clusters as there is no observations where both group members' efforts exceed 80 in one session collected during phase 1 of the *symm_loser* treatment. *, **, *** denotes statistical significance at the 10%, 5%, 1% level.

	(1) winner tournaments	(2) loser tournaments
Asym	25.908***	6.447
	(2.423)	(55.000)
Loss aversion	-0.210	1.644
	(0.853)	(5.927)
Risk seeking	-0.341	1.084
	(0.564)	(1.319)
Male	0.747	1.318
	(9.392)	(7.682)
Round	-0.866	-0.861
	(0.556)	(1.200)
Asym*Round	0.672*	-0.063
	(0.370)	(3.455)
Constant	42.548***	18.301
	(7.698)	(22.449)
Observations	401	146
Clusters	14	13

correct belief that both of their group members will overbid, the majority of subjects in the *asym_winner* treatment still fail to best respond by bidding less. Instead, they exhibit a strong and incorrect tendency to compete against their aggressive group members.[21]

In Appendix E.1, we present additional analysis aimed at assessing subjects' ability to best respond to their group members' efforts across all four treatments, regardless of whether the group members' efforts exceed 80. Furthermore, we examine whether subjects were able to respond effectively to their own guesses regarding their group members' efforts, which was elicited in round 20.

The influence of previous results on subjects' decision-making in rank order tournaments has been demonstrated in previous studies including Dutcher et al. (2015) and Gill et al. (2018). In Appendix E.2, we present a comprehensive analysis that examines how previous outcomes affect subjects' choices regarding effort allocation. Our findings highlight the significant impact of previous outcomes on subjects' provisions of effort. Specifically, in winner tournaments, subjects who won the immediately preceding round exhibited a substantial reduction in effort provision. In loser tournaments, subjects who lost in the immediately preceding round demonstrated an increase in their effort provision. However, that impact does not vary by the shock distribution.

5.2.2. Individual efforts in loser tournaments

In contrast to the findings observed in winner tournaments, the effort provisions exhibited by subjects in loser tournaments align with the ordinal relation predicted by the QRE. Furthermore, our results support the QRE distribution prediction presented in Fig. 3 (b), where no significant difference is observed in the effort provision within the intermediate range (i.e., 61-80) between the *asym_loser* and *symm_loser* treatments. To investigate how subjects should respond to their group members' effort in loser tournaments, Fig. 8 plots the calculation of subjects' best response effort given the group members' effort equals $e_1 = e_2 = e$.

[21] In a comparative analysis, it is noteworthy that among the 78 subjects in the *symm_winner* treatment, 13 individuals exhibited the belief that both of their group members would exert effort above 80. In response to this belief, 11 of those subjects exerted effort surpassing 65. This finding indicates that subjects in both the *asym_winner* and *symm_winner* treatments responded to a similar extent when they held the belief that both of their group members would overbid.

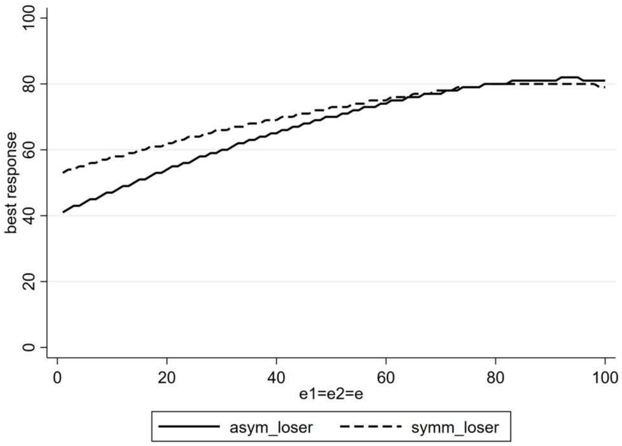


Fig. 8. Best response calculation. Note: the calculation is based on the assumption that both group members exert identical effort $e_1 = e_2 = e$.

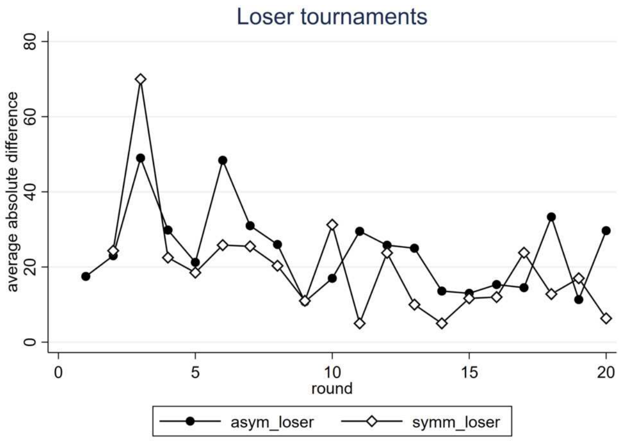


Fig. 9. The average absolute difference between the subject's effort and the best response, given that both of their group members' efforts are above 80, by treatment and round. Note: the *symm_loser* treatment only has 19 observations, the reason is because there are no such observations in round 1 where both group members' efforts are above 80.

An interesting distinction between the *asym_loser* and *asym_winner* treatments can be observed in Fig. 8. In the *asym_loser* treatment, subjects' responses to their opponents' overbidding behavior differ significantly compared to the *asym_winner* treatment. When their opponents exert excessively high efforts (i.e., greater than 80), the optimal strategy for subjects in the *asym_loser* treatment is to exert high effort (i.e., no less than 80) in order to compete against their opponents and avoid ending up in last place. This response is due to the significant difference in prizes between being last in the loser tournaments and not being first in the winner tournaments, as dictated by the optimal principal-agent contract scheme. Furthermore, our asymmetric shock design introduces the possibility of subjects experiencing highly negative shocks, which further reinforces their incentive to submit high efforts and prevent being last. In the case of symmetrically distributed random shocks, subjects in the *symm_loser* treatment would also need to exert exceptionally high efforts in response to their group members' aggressive behavior.

In order to examine whether subjects in loser tournaments effectively respond to their group members' overbidding behavior, we adopted the methodology outlined in Section 5.2.1. Specifically, we focused on a subgroup comprising observations where both group members' efforts exceeded 80. This subgroup consisted of a total of 146 observations, with 75 in the *asym_loser* treatment and 71 in the *symm_loser* treatment. On average, subjects in the *asym_loser* subgroup exerted an effort of 56.49, while those in the *symm_loser* subgroup exerted an effort of 66.13. There is slightly significant difference in the average effort provision between these two treatments (Wald test based on Column (2) of Table 3, $p = 0.072$). To further investigate the subject's response to their group members' overbidding, we calculated the absolute difference between the subjects' actual effort and their best responses in situations where both group members' efforts exceeded 80. The average absolute difference, aggregated by treatment and round, is presented in Fig. 9.

Fig. 9 demonstrates that there is no statistically significant difference in subjects' response to their group members' overbidding behavior between the *asym_loser* and *symm_loser* treatments. Moreover, Fig. 9 reveals a lack of a learning effect within the context of loser tournaments. Interestingly, as the sessions progressed, subjects demonstrated an inability to narrow the gap between their own effort levels and the corresponding best response. To confirm our findings, we conducted a regression analysis. The results are presented in Column (2) of Table 4 and provide additional support for the above observations.

Similar to the approach used in winner tournaments, we employed subjects' guesses regarding their group members' effort levels, as elicited in the last round, as a proxy for their group members' actual efforts. This allowed us to investigate whether subjects respond correctly to their beliefs. Among the 168 subjects participating in loser tournaments, 12 of them held the belief that both of their group members would exert effort above 80. Among these 12 subjects, 11 (4 in *asym_loser* and 7 in *symm_loser*) responded by exerting effort above 70. This aligns with predictions outlined in Fig. 8, indicating that when subjects hold the belief that their group members will engage in overbidding, they responded by exerting high effort in loser tournaments.

6. Conclusions

Rank order tournaments are ubiquitous and widely used in everyday life. As a result, they have been heavily investigated in experimental research. However, prior experimental literature has predominantly focused on the assumption that random shocks follow a symmetric distribution. This assumption represents an important limitation, particularly considering that many contestants deviate from expected equilibrium effort. Understanding how subjects respond to their opponents' off-equilibrium behavior becomes crucial, and such responses may vary depending on the specific shock distribution employed. In this paper, we use experimental methods to investigate subjects' behaviors under different random shock distributions.

In our experiments, we provided two different random shock distributions. The first is a symmetric (uniform) distribution, which is commonly used in tournament research. The second is an asymmetric (beta) distribution. We chose parameters to create a unimodal and negatively skewed distribution, allowing for subjects to realize extremely negative shocks. The asymmetric shock distribution can better capture features of tournaments including elite competitions, where performance clusters near the upper boundary but mistakes can be very costly. We also studied two different tournament structures, winner tournaments and loser tournaments, to investigate how subjects' behaviors change when the goal is to "strive to be first" or "avoid being last."[22]

In contrast to QRE predictions, we find no significant difference in average effort provision between winner tournaments. While consistent with the ordinal QRE predictions, subjects in *asym_loser* exerted no less effort than those in *symm_loser*. One reason for subjects in the winner tournaments failing to align with the QRE predictions is that subjects in the *asym_winner* treatment respond suboptimally to their group members' overbidding behavior. The theoretical prediction suggests that when both group members exert excessively high effort in the *asym_winner* treatment, subjects should respond by exerting extremely low effort. This response is justified by the rationale that, to compensate for the possibility of extremely negative shocks, the prize for not winning the winner tournament in the presence of asymmetric shock distribution is comparatively high. Consequently, subjects in the *asym_winner* treatment should have a stronger incentive to shy away from the competition compared to those in the *symm_winner* treatment. However, our data reveal that subjects in the *asym_winner* treatment fail to effectively respond to their group members' overbidding behavior. Despite both of their group members overbidding, there is no statistically significant difference in the effort provisions between the *asym_winner* and *symm_winner* treatments. In contrast, in the loser tournaments, the theory predicts no significant difference in the response to group members' overbidding behavior, and our experimental data align with this theoretical prediction.

Our study highlights the significance of investigating individual behavior within the asymmetric shock environment, particularly in situations where contestants deviate from equilibrium predictions. Theoretical predictions suggest that in winner tournaments, subjects should respond differently to their opponents' off-equilibrium behavior depending on the shock distribution. However, our research demonstrates that when the shocks exhibit negative skewness, subjects respond as aggressively as they do in the symmetric shock environment when confronted with opponents' overbidding. From the perspective of contest designers, our findings provide guidance for how to incentivize contestants to exert high effort in environments characterized by negatively skewed shocks. An important avenue for future research is to identify factors contributing to the ineffective response to opponents' off-equilibrium behavior within the asymmetric shock environment. This line of inquiry can provide deeper insights into the underlying mechanisms influencing contestants' behavior and decision-making in competitive settings.

Declaration of competing interest

This manuscript is financed by the National Science Foundation (SES-2048519) and the Interdisciplinary Center for Economic Science (ICES) at George Mason University (IRB Project Number: 1245427).

Data availability

Data will be made available on request.

[22] Note that in experiments testing predictions of contest theory almost always compare between contests with the same level of equilibrium effort. To ensure this can require changing the prize spread between types of contests. Dutcher et al. (2015), for example, change the spread in order to ensure the same equilibrium effort predictions between winner and loser tournaments. As noted in Table 1 above, we pursue the same approach across our tournament types. This is unavoidable if one wants to compare the same equilibrium effort predictions between treatments.

Appendix A. Optimal principal-agent contracts

Under our assumptions, the expected payoffs for subject i in the winner tournament can be written as:

$$\pi_i(e_i) = p_1^i(e_i) \times w_1 + [1 - p_1^i(e_i)] \times w_2 - c(e_i) \tag{A.1}$$

where $p_1^i(e_i)$ is the probability that subject i wins first place. If we take the derivative with respect to e_i, the first order condition becomes:

$$\frac{\partial p_1^i(e_i^*)}{\partial e_i} \times (w_1 - w_2) = c'(e_i^*) \tag{A.2}$$

where e_i^* is the Nash equilibrium effort in winner tournament.

Intuitively, that means that in equilibrium, the marginal cost for exerting one more unit of effort is equal to the marginal benefit for exerting one more unit of effort.

Using the same approach, for the loser tournament, the expected payoffs for subject i can be written as:

$$\pi_i(e_i) = p_n^i(e_i) \times v_2 + [1 - p_n^i(e_i)] \times v_1 - c(e_i) \tag{A.3}$$

where $p_n^i(e_i)$ is the probability of subject i coming in the last. Taking the derivative with respect to e_i, the first order condition becomes

$$\frac{\partial p_n^i(\overline{e_i})}{\partial e_i} \times (v_2 - v_1) = c'(\overline{e_i}) \tag{A.4}$$

where $\overline{e_i}$ is the Nash equilibrium effort in loser tournament.

We restrict our analysis to the symmetric case, where in equilibrium all subjects exert the same level of effort. Let $\beta_i = \frac{\partial p_i(e)}{\partial e}$ denote the derivative of the probability that an agent stays in ith place with respect to effort e. As shown by Akerlof and Holden (2012), β_i equals:

$$\beta_i = \frac{\partial p_i(e)}{\partial e} = \binom{n-1}{i-1} \int F(x)^{n-i-1}(1 - F(x))^{i-2}((n-i) - (n-1)F(x)) f(x)^2 dx \tag{A.5}$$

Specifically, when $i = 1$,

$$\beta_1 = (n-1) \int F(x)^{n-2} f(x)^2 dx \tag{A.6}$$

Plugging (A.6) back into (A.2), in a symmetric equilibrium, the F.O.C for the winner tournament becomes:

$$\left(w_1 - w_2\right) \times \beta_1 = c'(e^*) \tag{A.7}$$

When $i = n$,

$$\beta_n = -(n-1) \int (1 - F(x))^{n-2} f(x)^2 dx \tag{A.8}$$

If we plug (A.8) back into (A.4), in a symmetric equilibrium, the F.O.C for the loser tournament becomes:

$$-\left(v_1 - v_2\right) * \beta_n = c'(\bar{e}) \tag{A.9}$$

As in Lazear and Rosen (1981) and Dutcher et al. (2015), suppose the principal market is competitive, and thus that the expected payoffs for the principal are zero. Thus, the expected payoffs for the principal become:

$$\bar{\pi} = ne^* - w_1 - (n-1) w_2 = n\bar{e} - (n-1) v_1 - v_2 = 0 \tag{A.10}$$

Therefore, expected payoffs for agents in winner and loser tournaments now become:

$$\pi_i(e^*) = e^* - c(e^*) \tag{A.11}$$

$$\pi_i(\bar{e}) = \bar{e} - c(\bar{e}) \tag{A.12}$$

Suppose that the principal chooses the prize structures, w_1 (v_1) and w_2 (v_2), that maximizes agents' expected payoffs. This implies,

$$(1 - c'(e^*)) \frac{\partial e^*}{\partial w_k} = (1 - c'(\bar{e})) \frac{\partial \bar{e}}{\partial v_k} = 0, \quad k = 1, 2 \tag{A.13}$$

To conclude the model, for winner tournaments we have:

$$\left(w_1 - w_2\right) * \beta_1 = c'\left(e^*\right), \quad ne^* - w_1 - (n-1) w_2 = 0, \quad c'(e^*) = 1$$

For the loser tournament, we have:

$$-\left(v_1 - v_2\right) * \beta_n = c'(\bar{e}), \quad n\bar{e} - (n-1) v_1 - v_2 = 0, \quad c'(\bar{e}) = 1$$

Appendix B. Experimental instructions (*asym_winner*)

Welcome to this experiment on decision making. You've already earned a $5 show-up bonus. We thank you for your participation!

The experiment will be conducted on the computer. All decisions and answers will remain confidential and anonymous. Please do not talk to each other during the experiment. If you have any question, please raise your hand and an experimenter will assist you.

During the experiment, you and the other participants will be asked to make a series of decisions. Your payment will be determined by your decisions as well as the decisions of the other participants according to the following rules.

During the first part of the experiment, you will be earning tokens. At the end of the experiment, tokens will be converted to US dollars at a rate of 2000 tokens = 1 US dollar. Today's experiment consists of several parts. The instructions for part 1 are given below. You will receive further instructions for other parts after you completing part 1.

Rounds and groups:

The first part consists of 20 rounds. The computer will choose four rounds at random for which you will be paid. You will not be told which rounds will be paid until the conclusion of all parts of the experiment.

At the beginning of each round, you will be randomly matched in a group with 2 other participants. This means that in each round the groups are randomly re-matched. During the experiment you will be assigned an ID number. The experimenter will use this ID number to match your decisions with your payments. You will never be told the ID numbers of those in your group and they will never be told your ID number.

Tasks:

In each round, you need to choose a number between 1 and 100 (e.g. 1,2,3… …100). You will enter your chosen number in the blank box on your computer screen labeled "Number Chosen" and then hit "Continue". The sheet labeled "Decision Costs" (Table B.3) shows you the cost in tokens associated with each number (1,2……100). Look at the sheet and you will find that choosing higher numbers means you will incur a higher cost. Everyone has the same cost sheet as yours. In each round, all group members choose her/his numbers simultaneously. You will not know the number chosen by any of your group members when you make your choice and likewise, they will not know the number you choose when they make their choice.

After all group members have made their choice, the computer will draw a random number, between -67.00 to 33.00, independently for each member of your group. **Different numbers have different chances to be drawn.** The chance for each number to be drawn from this range has the shape in Fig. B.1 below.

At the beginning of part 1, you will be given several examples to help you get a better understanding of the shape described above.

Here are the brief descriptions regarding the characteristics of these random numbers:

(1) The highest number you can possibly draw is 33;
(2) The lowest number you can possibly draw is -67;
(3) Over the 20 rounds, most people will see at least one draw below -33;
(4) Your previous draws do not affect your future draws at all;
(5) Your draws do not affect your group members' draws, and their draws do not affect your draws.

If the number you draw is positive (negative), then it will be added (subtracted) from your chosen number to make your total number.

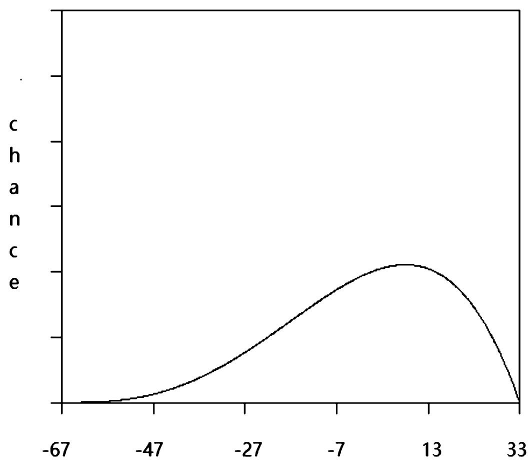


Fig. B.1. The chance for each number to be drawn.

Table B.1
Example 1.

	Number chosen (A)	Random number (B)	Total number (A+B)
You	50	1	51
Your group member 1	32	17	49
Your group member 2	80	-45	35

Table B.2
Example 2.

	Number chosen (A)	Random number (B)	Total number (A+B)
You	40	1	41
Your group member 1	32	17	49
Your group member 2	80	-45	35

Table B.3
Decision Cost.

Number	Cost	Number	Cost	Number	Cost	Number	Cost
1	5	**26**	179	**51**	532	**76**	1535
2	10	**27**	188	**52**	553	**77**	1612
3	16	**28**	198	**53**	575	**78**	1695
4	21	**29**	208	**54**	599	**79**	1785
5	27	**30**	219	**55**	623	**80**	1881
6	32	**31**	229	**56**	648	**81**	1985
7	38	**32**	240	**57**	675	**82**	2097
8	44	**33**	251	**58**	702	**83**	2220
9	50	**34**	263	**59**	731	**84**	2353
10	56	**35**	275	**60**	761	**85**	2498
11	63	**36**	287	**61**	793	**86**	2657
12	69	**37**	300	**62**	826	**87**	2833
13	76	**38**	313	**63**	861	**88**	3027
14	82	**39**	327	**64**	897	**89**	3242
15	89	**40**	341	**65**	936	**90**	3482
16	97	**41**	355	**66**	976	**91**	3752
17	104	**42**	370	**67**	1019	**92**	4056
18	111	**43**	386	**68**	1064	**93**	4402
19	119	**44**	402	**69**	1111	**94**	4797
20	127	**45**	418	**70**	1161	**95**	5255
21	135	**46**	435	**71**	1214	**96**	5788
22	143	**47**	453	**72**	1271	**97**	6416
23	152	**48**	472	**73**	1330	**98**	7166
24	161	**49**	491	**74**	1394	**99**	8076
25	170	**50**	511	**75**	1462	**100**	9197

Payoffs:

The computer will compare your total number with the total number of those in your group. The person with the **highest** total number will receive 11,850 tokens while the remaining 2 members of the group will receive 6,075 tokens. The cost of each chosen number will be subtracted from the raw payoffs to give you the payment for each round. Remember, only 4 out of 20 rounds will be randomly chosen for payment.

At the end of each round you will be shown the random number chosen for you, your resulting total number, and whether your total number is higher than others in your group.

Examples:

Let's go through an example. Suppose the Table B.1 shows the results for you and your group members in one round.

In this round, you chose the number 50 and the other members of your group chose 32, 80. Also suppose that the random number drawn for you was 1 and the random number drawn for the other members of your group were 17 and -45 respectively. This would mean your total number is $50 + 1 = 51$. The total number of the other group members would be $32 + 17 = 49$ and $80 + (-45) = 35$. In this example, you have the highest total number and the cost associated with a chosen number of 50 is 511, thus you would receive $11,850 - 511 = 11,339$ tokens if this round was randomly chosen for payment.

Let's look at another example: in this round, you had chosen 40 and all other chosen numbers and random draws remained the same, then the results would become in Table B.2:

In this case, you have a total number of 40+1 = 41. This would mean someone else would have the highest total number and the cost associated with a chosen number of 40 is 341, thus you would receive $6,075 - 341 = 5,734$ tokens if this round was randomly chosen for payment.

Once you have made your decisions or are finished viewing the results, please click the continue button. No one can move to the next round until everyone in the experiment has clicked on this button so make sure to pay attention to the screen to keep the experiment moving along.

This is the end of the instructions. You will be given a short quiz to ensure that you understand the instructions. Once you complete the quiz successfully, you'll proceed to the experiment.

Appendix C. Examples (the asymmetric distribution)

Here are the examples that can help you get a better understanding of the shape and characteristics of random numbers mentioned in the instructions.

These examples only let you get familiar with the shape and characteristics of the random numbers. They are independent of Part 1 and will not be paid.

The table below shows 100 numbers that computer drawn from the same range we mentioned in the instructions:

Round 1-10
12.95
-29.72
8.97
1.93
-14.05
10.95
5.13
-6.95
-28.11
-12.59

Round 11-20
-4.53
-20.59
-53.09
20.16
-26.46
17.39
17.66
9.0
-5.24
23.84

Round 21-30
19.86
16.12
7.52
1.39
-19.6
8.35
21.49
8.32
-31.2
9.62

Round 31-40
7.96
8.57
-32.56
12.87
6.09
1.16
26.19
-18.61

-38.73
-11.06

Round 41-50
-3.39
-10.96
-13.13
-0.91
10.15
-4.45
-19.68
-10.78
-26.72
-11.18

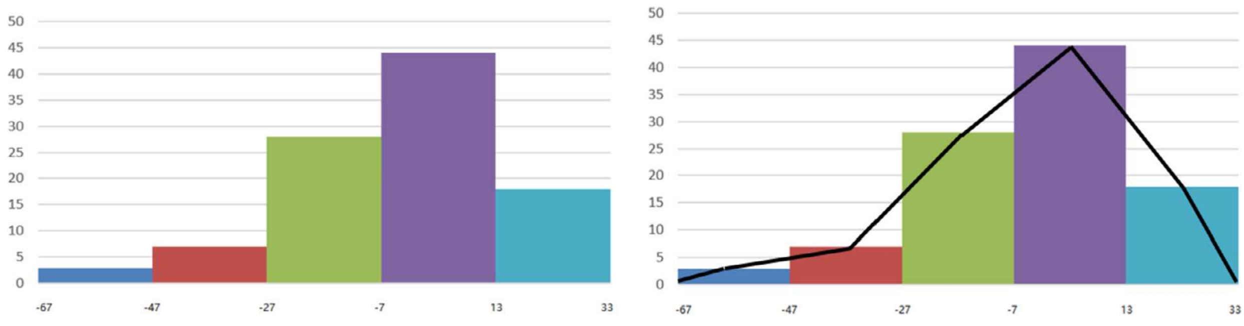
Round 51-60
-0.84
-18.12
-7.92
-20.9
1.75
5.94
10.58
13.33
-42.41
-3.71

Round 61-70
22.0
-10.04
-17.49
-21.87
4.17
-7.58
-3.03
-10.25
31.14
17.9

Round 71-80
26.38
7.64
-23.44
-4.85
-18.49
-45.3
-9.19
-2.28
4.10
20.54

Round 81-90
24.04
-7.68
-2.3
1.01
7.68
10.82
-13.85
-19.91
3.03
18.50

Round 91-100



(a) (b)

Fig. C.1. The histogram of these randomly drawn numbers.

-30.2
-17.64
4.47
5.21
-2.98
15.79
11.94
12.16
22.7
-28.63

You may feel tedious on reading these numbers. So I list a brief summary about the characteristics of these numbers.
The highest number among these 100 numbers is: 31.14(Round 69);
The lowest number among these 100 numbers is: -53.09 (Round 13);
The number of random draws fall between -67 to -47:3;
The number of random draws fall between -47 to -27: 7;
The number of random draws fall between -27 to -7:28;
The number of random draws fall between -7 to 13:44;
The number of random draws fall between 13 to 33:18;

More intuitively, Fig. C.1(a) shows several rectangles: the height of each rectangle represents the number of draws that falls in this certain range.

If we use lines to connect the upper-middle points in each rectangle in Fig. C.1(a), then we can get the similar shape (as shown in Fig. C.1(b)) mentioned in the instructions.

This is the end of the examples. If you have any question, please raise your hand, an experimenter will assist you.

Any questions?

Appendix D. QRE predictions

Table D.1 shows the QRE expected efforts under different values of noise parameter, λ.

As we can find that, among the parameters we selected, $\lambda = 20$ fits our observations best, that is, it generates the smallest sum of absolute difference between the predicted value and the observed value across treatments. Therefore, we use that noise parameter to make the corresponding QRE predictions.

Table D.1
QRE estimations.

	asym_winner	*symm_winner*	*asym_loser*	*symm_loser*
$\lambda = 0.02$	48.76	48.80	48.78	48.80
$\lambda = 0.2$	48.90	49.21	49.04	49.22
$\lambda = 2$	50.43	53.07	52.34	53.82
$\lambda = 20$	63.91	71.23	75.26	74.86
$\lambda = 200$	77.19	79.03	79.64	79.35
Observations	63.70	64.65	62.85	63.58

Table E.1
Summary statistics of subjects by collection phase, the standard deviations are shown in parentheses. Risk seeking indicates the number of risky choices subjects made in the risk aversion task; Loss aversion indicates the number of lotteries subjects refused to play in the loss aversion task.

	date	# of subjects	fraction of male	risk seeking	loss aversion
Phase 1	06/2018 – 10/2018	192	0.59	4.96	2.95
			(0.49)	(2.14)	(1.44)
Phase 2	11/2022	144	.47	4.57	2.96
			(0.50)	(2.32)	(1.66)

Table E.2
Summary statistics of subjects by treatment, the standard deviations are shown in parentheses. Risk seeking indicates the number of risky choices subjects made in the risk aversion task; Loss aversion indicates the number of lotteries subjects refused to play in the loss aversion task.

	# of subjects	fraction of male	risk seeking	loss aversion
asym_winner	90	0.56	4.78	3.2
		(0.49)	(2.21)	(1.54)
symm_winner	78	0.55	5.28	2.49
		(0.49)	(2.46)	(1.54)
asym_loser	87	0.58	4.44	2.64
		(0.49)	(2.29)	(1.47)
symm_loser	81	0.47	4.74	2.98
		(0.50)	(1.83)	(1.53)

Table E.3
Summary statistics of random shocks by treatment.

	observation	mean	standard deviation	minimum	maximum
asym_winner	1800	0.32	18.11	−54.38	31.83
symm_winner	1560	0.14	29.00	−49.99	49.97
asym_loser	1740	−0.24	18.17	−52.69	31.73
symm_loser	1620	−0.13	29.37	−49.93	49.99

Appendix E. Supplementary data analysis

E.1. Best response

To investigate whether subjects were best responding to their group members' off-equilibrium efforts, as well as whether they could learn through the experiment, we obtain subjects' best responses, according to their group members' efforts. Then, we calculate the absolute difference between subjects' effort and their best responses. The absolute difference, averaged by treatment and round is shown in Fig. E.1 below.

Differences in behavioral patterns were observed among subjects across different treatments. In winner tournaments, when considering all observations, subjects in the *asym_winner* treatment showed slightly poorer performance in terms of best responding

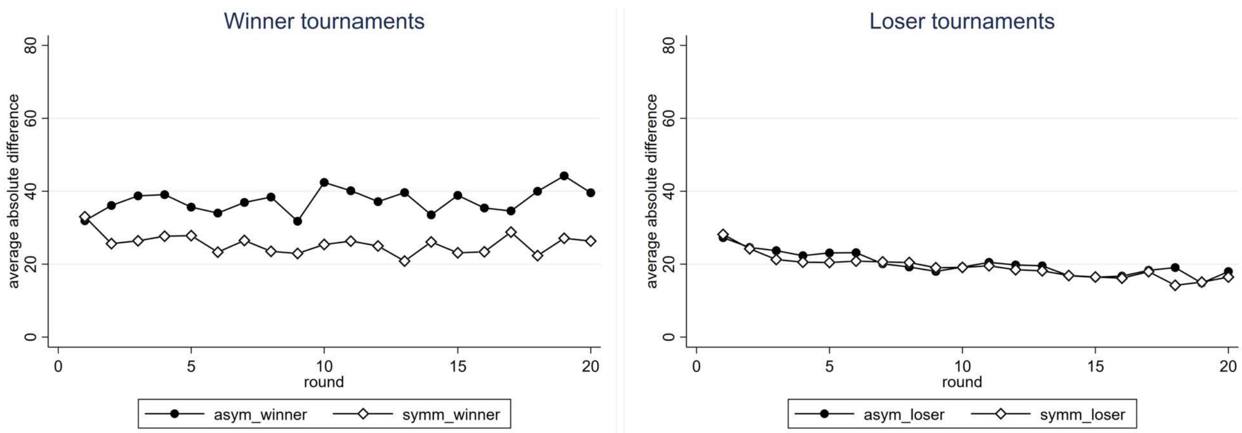


Fig. E.1. The average absolute difference between the subject's effort and the best response by round in (a) winner tournaments and (2) loser tournaments.

Table E.4
OLS regression analysis on whether the random shocks were drawn similarly across all sessions. The dependent variable is the random shock drawn in the (1)*asym_winner* (2) *symm_winner* (3) *asym_loser* and (4) *symm_loser* treatments. Independent variable is the categorial variable at the session level, and uses the first session in each treatment as the reference group. *, **, *** denotes statistical significance at the 10%, 5%, 1% level.

	(1) *asym_winner*	(2) *symm_winner*	(3) *asym_loser*	(4) *symm_loser*
Session 2	1.445 (1.478)	2.944 (2.647)	0.851 (1.791)	−5.327* (3.092)
Session 3	1.878 (1.706)	4.339 (2.859)	1.828 (1.712)	0.008 (2.892)
Session 4	−1.154 (1.478)	1.036 (2.859)	2.794 (1.712)	2.875 (2.765)
Session 5	−0.501 (1.567)	1.271 (2.647)	−1.124 (1.791)	−2.053 (2.892)
Session 6	1.259 (1.567)	5.604** (2.647)	0.412 (1.791)	−0.609 (2.892)
Session 7	−1.266 (1.567)	2.23 (2.647)	1.206 (1.791)	0.901 (2.892)
Constant	0.155 (1.045)	−2.333 (1.872)	−1.224 (1.354)	0.19 (2.186)
Observations	1800	1560	1740	1620

Table E.5
Statistical analysis of effort provision across treatments. Note: The Mann-Whitney tests utilize the average fraction of subjects exerting effort in the range of 1-10 (91-100/61-80) per session as the unit of observation. Each treatment is composed of 7 independent observations. The Wald tests are conducted based on logit regression, with standard errors clustered at the session level and with the BRL adjustment. The dependent variable is a binary variable that indicates whether a subject exerted effort in the range of 1-10 (91-100/61-80). The independent variables include the treatment dummy, time trend, the gender of the subject, as well as their risk and loss preferences.

	Mann-Whitney test	Wald test
Effort between 1-10: asym_winner vs. symm_winner	p = 0.926	p = 0.378
Effort between 91-100: asym_winner vs. symm_winner	p = 0.026	p = 0.019
Effort between 61-80: asym_loser vs. symm_loser	p = 0.535	p = 0.917

compared to those in the *symm_winner* treatment (Wald test based on Column (1) in Table E.6, $p = 0.592$). Moreover, there was no evidence of a learning effect in winner tournaments, as subjects' efforts did not converge towards their best responses as the session progressed. This finding reinforces the notion that the primary divergence in subjects' behavior between the *asym_winner* and *symm_winner* treatments lies in their responses to their group members' overbidding behavior.

In loser tournaments, we find no significant difference in deviations from best responses between subjects in the *asym_loser* and *symm_loser* treatments (Wald test based on Column (2) in Table E.6, $p = 0.778$). Moreover, subjects demonstrated learning throughout the session, with their efforts gradually aligning with their best responses as the session progressed and such learning process exhibited no significant difference between the treatments.

For all four treatments, the deviations between subjects' efforts and their corresponding best responses were significantly greater than zero (Wald test based on Columns (1) and (2) in Table E.6, $p < 0.01$ for all four comparisons). This indicates that subjects did not achieve their best response in relation to their group members' efforts.

As stated in Dutcher et al. (2015), one possible explanation for the suboptimal performance at best-responding, particularly in the *asym_winner* treatment, is the formation of inaccurate beliefs. Following the methodology employed by Dutcher et al. (2015), we utilized a similar approach in the final round of our study. Specifically, we asked subjects to indicate their perceptions of their group

Table E.6
OLS regressions with standard errors clustered at the session level and adjusted for the small number of clusters using the Bias-Reducing Linearization procedure (BRL) of Bell and McCaffrey (2002). The dependent variable is the absolute difference between effort and best response in Columns (1) and (2), in Columns (3) and (4), the dependent variable is the absolute difference between effort and best response to beliefs in the last period. The independent variables in the model include a treatment dummy, with the asymmetric shock treatment serving as the reference group. Additionally, we controlled for the time trend, the interaction between the time trend and the treatment dummy, the gender of the subjects, and their levels of risk-seeking and loss aversion. Risk seeking indicates the number of risky choices subjects made in the risk aversion task; Loss aversion indicates the number of lotteries subjects refused to play in the loss aversion task. *, **, *** denotes statistical significance at the 10%, 5%, 1% level.

	(1) winner tournaments	(2) loser tournaments	(3) winner tournaments	(4) loser tournaments
Asym	8.321% (15.518)	0.302 (1.071)	5.144 (13.231)	-1.396 (6.946)
Loss aversion	-0.501* (0.266)	-0.448 (0.274)	0.077 (2.544)	-1.035*** (0.392)
Risk seeking	0.022 (1.520)	0.367 (0.400)	-0.011 (2.004)	-0.098 (1.078)
Male	2.949 (2.330)	1.844*** (0.415)	7.147* (4.141)	1.045 (5.524)
Round	-0.156 (0.443)	-0.483*** (0.026)		
Asym*Round	0.368 (1.714)	0.025 (0.020)		
Constant	26.721*** (5.354)	23.017*** (2.970)	27.325 (21.541)	18.615** (8.062)
Observations	3360	3360	168	168
Clusters	14	14	14	14

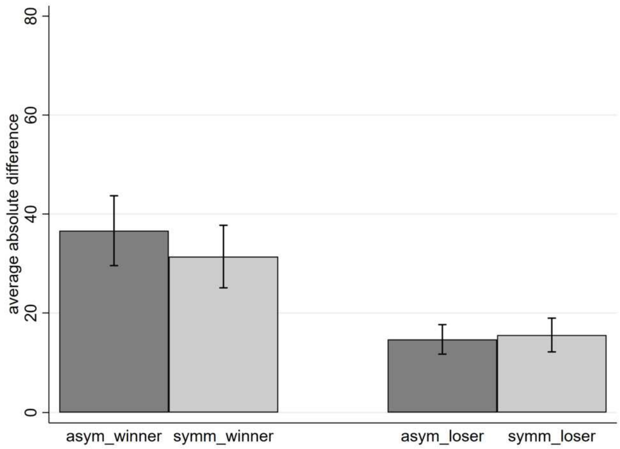
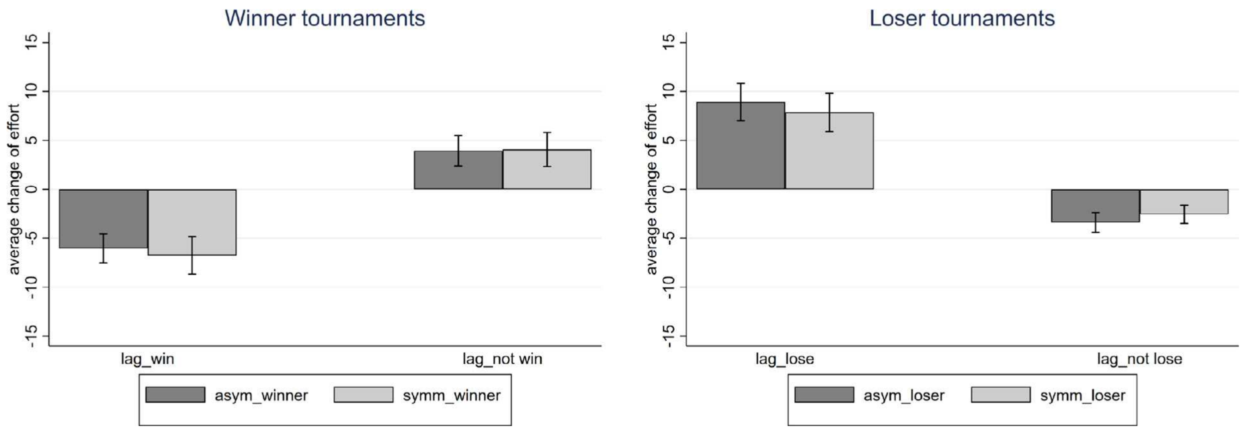


Fig. E.2. The average absolute difference between subject's effort and their best response to their beliefs. Note: We use subjects' last rounds guesses on their group members' efforts as their beliefs on their group members' efforts. The error bars in the figure represent the 95% confidence intervals around the average absolute difference between subjects' effort and their best response to their beliefs on group members' effort.

members' choices in the final round through an incentivized method.[23] We used these beliefs as a proxy for their group members' efforts and examined whether subjects best responded to these beliefs. Fig. E.2 illustrates the average absolute difference between subjects' efforts and their best response based on their beliefs about their group members' efforts, categorized by treatment.

As depicted in Fig. E.2, our analysis reveals that subjects do not optimally best respond to their beliefs about their group members' efforts. When comparing within the winner tournaments, we find no significant difference in deviations between subjects' efforts and their best responses based on their beliefs between the *asym_winner* and *symm_winner* treatments (Wald test based on Column (3) of

[23] To be precise, for each of the subject's guesses, if the difference between their guess and their group member's choice was within 5, the subject's guess was considered correct and entailed an additional $2 reward.



(a) winner tournaments (b) loser tournaments

Fig. E.3. Average change of effort in (a) winner tournaments after winning (lag_win) or not winning (lag_not win) in the previous round and in (b) loser tournaments after losing (lag_lose) or not losing (lag_not lose) in the previous round. The error bar represents the corresponding 95% confidence interval.

Table E.7
Individual random effect panel regression with standard errors clustered at the individual level. The dependent variable is the change in efforts in (1) winner tournaments and (2) loser tournaments. Lag win (lose) is the binary variable indicates whether subjects win (lose) in the previous round in winner (loser) tournaments; Asym equals 1 if the random shocks are asymmetrically distributed in treatments, and 0 if the random shocks are symmetrically distributed; Risk seeking indicates the number of risky choices subjects made in the risk aversion task; Loss aversion indicates the number of lotteries subjects refused to play in the loss aversion task. Clustered standard errors, are shown in parentheses. *, **, *** denotes statistical significance at the 10%, 5%, 1% level.

	(1) winner tournaments	(2) loser tournaments
Asym	0.207	-0.183
	(0.345)	(0.281)
Lag win (lose)	-12.217***	12.879***
	(1.443)	(1.175)
Number of times win (lose)	0.865***	-0.813***
	(0.139)	(0.119)
Loss aversion	-0.107	0.087
	(0.111)	(0.098)
Risk seeking	-0.043	-0.005
	(0.063)	(0.065)
Male	0.345	0.048
	(0.319)	(0.286)
Round	-0.518***	0.064
	(0.071)	(0.047)
Constant	7.358***	-1.360*
	(0.937)	(0.747)
Observations	3192	3192
Clusters	168	168

Table E.6, $p = 0.698$). However, it is noteworthy that both deviations are significantly greater than zero (Wald test based on Column (3) of Table E.6, $p < 0.01$ for both comparisons). A similar behavioral pattern is observed in the analysis of loser tournaments: there is no significant difference in deviations between treatments (Wald test based on Column (4) of Table E.6, $p = 0.841$), while both deviations are significantly greater than zero (Wald test based on Column (4) of Table E.6, $p < 0.05$ for both comparisons). These findings align with the results reported by Dutcher et al. (2015), indicating that even in the final round, subjects did not consistently best respond to their own stated incentivized beliefs.

E.2. How the previous outcome affects subjects' effort choice

Fig. E.3 (a) shows the average change in effort after winning (not winning) the immediately preceding round in winner tournaments. We find that winning (not winning) the immediately preceding round significantly impacted subject's effort provision. In particular, if subjects won the preceding round, they reduced their efforts; if they did not win the preceding round, they increased their efforts. However, these differences did not vary by treatment. The regression analysis on Column (1) of Table E.7 further confirms our findings.

Fig. E.3 (b) demonstrates the average change in effort based on losing (not losing) the preceding round in loser tournaments. Subjects in loser tournaments demonstrated similar behavioral patterns to those in winner tournaments: If subjects lost the immediately preceding round, they increased their effort. If subjects did not lose the immediately preceding round, they reduced their effort. There was no significant treatment difference. Table E.7 on Column (2) confirms our findings.

Our findings align with those reported by Dutcher et al. (2015) but diverge from the observations made by Gill et al. (2018). One potential explanation for this discrepancy could be attributed to differences in the payment schemes employed. Both our study and Dutcher et al. (2015) utilized a "tournament" payment scheme, whereby subjects' payoffs were contingent on both their output and the level of effort exerted. In this scheme, higher levels of effort incurred higher costs. Conversely, Gill et al. (2018) adopted a "flat wage" payment scheme, which remained independent of subjects' effort provision. Furthermore, in our experimental design as well as Dutcher et al. (2015) and Gill et al. (2018), subjects were only provided information about their own output and relative ranking, with no knowledge of their group members' output. This design choice highlights the heterogeneous influences of relative ranking on subjects' effort provisions under different payment schemes.[24]

Appendix F. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2023.10.008.

References

Akerlof, Robert J., Holden, Richard T., 2012. The nature of tournaments. Econ. Theory 51 (2), 289–313.

Bell, Robert M., McCaffrey, Daniel F., 2002. Bias reduction in standard errors for linear regression with multi-stage samples. Surv. Methodol. 28 (2), 169–182.

Bhattacharya, Sudipto, 1985. Tournaments, Termination Schemes, and Forcing Contracts.

Bull, Clive, Schotter, Andrew, Weigelt, Keith, 1987. Tournaments and piece rates: an experimental study. J. Polit. Econ. 95 (1), 1–33.

Cason, Timothy N., Masters, William A., Sheremeta, Roman M., 2020. Winner-take-all and proportional-prize contests: theory and experimental results. J. Econ. Behav. Organ. 175, 314–327.

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

Drago, Robert, Heywood, John S., 1989. Tournaments, piece rates, and the shape of the payoff function. J. Polit. Econ. 97 (4), 992–998.

Drugov, Mikhail, Ryvkin, Dmitry, 2020. Tournament rewards and heavy tails. J. Econ. Theory 190, 105116.

Dutcher, E. Glenn, Balafoutas, Loukas, Lindner, Florian, Ryvkin, Dmitry, Sutter, Matthias, 2015. Strive to be first or avoid being last: an experiment on relative performance incentives. Games Econ. Behav. 94, 39–56.

Eriksson, Tor, Teyssier, Sabrina, Villeva, Marie-Claire, 2009. Self-selection and the efficiency of tournaments. Econ. Inq. 47 (3), 530–548.

Fang, Dawei, Noe, Thomas, Strack, Philipp, 2020. Turning up the heat: the discouraging effect of competition in contests. J. Polit. Econ. 128 (5), 1940–1975.

Fischbacher, Urs, 2007. z-Tree: Zurich toolbox for ready-made economic experiments. Exp. Econ. 10 (2), 171–178.

Gächter, Simon, Johnson, Eric J., Herrmann, Andreas, 2007. Individual-Level Loss Aversion in Riskless and Risky Choices.

Gerchak, Yigal, He, Qi-Ming, 2003. When will the range of prizes in tournaments increase in the noise or in the number of players? Int. Game Theory Rev. 5 (02), 151–165.

Gill, David, Kissová, Zdenka, Lee, Jaesun, 2018. First-place loving and last-place loathing: how rank in the distribution of performance affects effort provision. Manag. Sci. 65 (2), 494–507.

Green, Jerry R., Stokey, Nancy L., 1983. A comparison of tournaments and contracts. J. Polit. Econ. 91 (3), 349–364.

Hartig, Bjoern, Reitzner, Matthias, 2017. Production Shock Distribution and Risk Aversion in Multi-Agent-Tournaments. Available at SSRN 3066454.

Hill, Denise M., Hanton, Sheldon, Matthews, Nic, 2010. Choking in sport: a review. Int. Rev. Sport Exerc. Psychol. 3 (1), 24–39.

Holt, Charles A., Laury, Susan K., 2002. Risk aversion and incentive effects. Am. Econ. Rev. 92 (5), 1644–1655.

Lazear, Edward P., 1999. Personnel economics: past lessons and future directions presidential address to the society of labor economists, San Francisco, May 1, 1998. J. Labor Econ. 17 (2), 199–236.

Lazear, Edward P., Rosen, Sherwin, 1981. Rank-order tournaments as optimum labor contracts. J. Polit. Econ. 89 (5), 841–864.

List, John A., van Soest, Daan, Stoop, Jan, 2020. On the role of group size in tournaments: theory and evidence from laboratory and field experiments. Manag. Sci.

Mago, Shakun D., Sheremeta, Roman M., 2019. New Hampshire effect: behavior in sequential and simultaneous multi-battle contests. Exp. Econ. 22 (2), 325–349.

Mago, Shakun D., Sheremeta, Roman M., Yates, Andrew, 2013. Best-of-three contest experiments: strategic versus psychological momentum. Int. J. Ind. Organ. 31 (3), 287–296.

Mago, Shakun D., Samak, Anya C., Sheremeta, Roman M., 2016. Facing your opponents: social identification and information feedback in contests. J. Confl. Resolut. 60 (3), 459–481.

McKelvey, Richard D., Palfrey, Thomas R., 1995. Quantal response equilibria for normal form games. Games Econ. Behav. 10 (1), 6–38.

McLaughlin, Kenneth J., 1988. Aspects of tournament models: a survey. Res. Labor Econ. 9 (1), 225–256.

[24] We thank an anonymous referee for suggesting this point.

Mirrlees, James A., 1999. The theory of moral hazard and unobservable behaviour: Part I. Rev. Econ. Stud. 66 (1), 3–21.
Moldovanu, Benny, Sela, Aner, Shi, Xianwen, 2012. Carrots and sticks: prizes and punishments in contests. Econ. Inq. 50 (2), 453–462.
Sheremeta, Roman M., 2010. Experimental comparison of multi-stage and one-stage contests. Games Econ. Behav. 68 (2), 731–747.
Sheremeta, Roman M., 2013. Overbidding and heterogeneous behavior in contest experiments. J. Econ. Surv. 27 (3), 491–514.
Shupp, Robert, Sheremeta, Roman M., Schmidt, David, Walker, James, 2013. Resource allocation contests: experimental evidence. J. Econ. Psychol. 39, 257–267.
Song, Jian, Houser, Daniel, 2021. Non-exclusive group contests: an experimental analysis. J. Econ. Psychol. 87, 102444.
Thomas, Jonathan P., Wang, Zhewei, 2013. Optimal punishment in contests with endogenous entry. J. Econ. Behav. Organ. 91, 34–50.