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Daniel Houser and Jian Song

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Interdisciplinary Center for Economic Science
4400 University Drive, MSN 1B2, Fairfax, VA 22030
Tel: +1-703-993-4850 Fax: +1-703-993-4851
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Asymmetric Shocks in Contests: Theory and Experiment*

Jian Song† Daniel Houser‡

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ABSTRACT

Under optimal tournament design, we would expect agents to exert identical effort regardless of the shape of the contest function's error component. We report data from laboratory experiments that provide a first test of this prediction. We find that efforts do not significantly differ when the shock distribution exhibits negative skewness versus a uniform distribution; however, subjects react substantially differently to random shock realizations under different treatments. Specifically, tournament winners demonstrate stronger reactions, economically and statistically, to negatively-skewed shocks than to uniform shocks. Meanwhile, tournament losers are less likely to be affected by negatively-skewed shocks. Our results highlight the importance of accounting for the influence of the shape of the shock distribution on a contest participant's effort.

Keywords: Asymmetric random shock, Tournament, Winner, Loser, Laboratory experiment

JEL classification: D90, M52, C90

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†Department of Economics and Interdisciplinary Center for Economic Science, George Mason University, Fairfax, VA, United States. Email: jsong25@masonlive.gmu.edu

‡Department of Economics and Interdisciplinary Center for Economic Science, George Mason University, Fairfax, VA, United States. Email: dhouser@gmu.edu

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 & Rosen (1981). This theory literature develops "contest functions", which include a deterministic component and an additively-separable stochastic component, referred to as the "shock". Although the literature highlights the fact that effort exerted by agents should not vary with the shape of the shock distribution under the optimal principal-agent contracts, it is somewhat surprising that all of the empirical/experimental literature informing this theory focuses on environments with symmetric 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 an athlete will suffer an extremely negative shock (perhaps due to "choking"[1]). Symmetric shock distributions do not capture this phenomenon.

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 *25m 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, with a few very low scores that 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 up this challenge.

Using the seminal theory framework of Lazear & 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 in practice.

Economic theory predicts that tournament participants' efforts should be invariant to

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

[2]The optimal principal-agent contracts are characterized by: (1) The agents choose the 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.

shock distributions. In practice, however, random shock realizations may impact participants' decisions. Previous studies suggest that even when people know the data-generating process is random ex ante, they tend to form incorrect beliefs that their past performance can predict their future performances (e.g. Powdthavee & Riyanto (2015)). Few studies have investigated which factors affect the extent of such incorrect beliefs. One of our goals is to explore whether different shock distributions influence the extent of incorrect beliefs about the threat of negative shocks. That is, if subjects know that they have a greater chance of facing extremely negative shocks ex ante, when facing (even not extremely) negative shocks in tournaments, they may overestimate (underestimate) the threat of facing negative shocks in the future. We would not expect the same result when subjects know the shock distribution is symmetric.

We conducted experiments with treatments that differed in both the shock distribution and the tournament structure. 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 bigger 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[3].

Further, we compare tournament winners' (losers') behavior under different distributions of random shocks. Winners' (Losers') decisions have been heavily investigated in the literature. A common finding is that tournament winners' (losers') effort varies significantly (see Dechenaux *et al.* (2015)). Our study provides evidence on whether this empirical result is robust to the specification of the shock distribution.

We find that shock realizations impact future effort decisions. Further, tournament win-

[3]There are some studies that investigate the impact of strategic momentum on subjects' behavior (e.g. Mago *et al.* (2013); Mago & 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."

ners and losers react differently, economically and statistically, to shocks, and their reaction varies according to the nature of shock distribution. In winner tournaments, tournament winners demonstrate stronger reactions to negative-skewed shocks than symmetric shocks. By contrast, in loser tournaments with negative-skewed shock treatments, tournament losers are less responsive to previous shock realizations[4].

We believe the observed differences result from heterogeneity in incorrect beliefs on previous shock realizations. Specifically, winners in asymmetric shock treatments know that they could face extremely negative shocks. If they suffered such a shock in a previous round, they are more likely to hold incorrect beliefs in positive autocorrelation of the independent random shocks. That is, they believe they will face extremely negative shocks in subsequent rounds[5]. As a result, they exert greater effort to win the tournament. However, in contrast to winners in winner tournaments, losers in losers tournaments in asymmetric shock treatments are less likely to hold such beliefs. Even when they experienced a negative (positive) shock in the previous round, they are less likely to believe that they will suffer a similar "bad" ("good") shock in the current round. As a result, they do not increase (decrease) their efforts as much as those in a symmetric shock treatment.

We find statistically significant evidence supporting these hypotheses. These findings emphasize the importance of conducting empirical/experimental investigations into theoretical models of asymmetric shock tournaments. Likewise, they are in line with the reality that in "elite" tournaments, to win the gold medal, top athletes may amplify their failures and exert greater effort. In contrast, the performance of athletes who do not belong to the top-level is not likely to fluctuate much, as their goal is only avoid losing.

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 & Rosen (1981), the contest literature extensively explored the theoretical foundation of rank-order tournaments (Green & 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.

[4]Some may argue that, winning is not randomly assigned because subjects who exert a higher effort are more likely to win. To control such effect, we classify "winner" ("loser") by using whole session results and make comparison only within the "winner" ("loser") group.

[5]When random shocks are symmetric, such incorrect belief still exists among tournament winners, but in a less strong extent compared with asymmetric treatment.

The literature has extensively investigated how optimal prize structures vary with shock distributions: Gerchak & 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 & Holden (2012) and Hartig & Reitzner (2017) both provided theoretical investigations of rank-order tournaments where random shocks were asymmetrically distributed. While Akerlof & Holden (2012) focused on how shock distribution affects the magnitude of prize structures, Hartig & Reitzner (2017) analyzed how shock distribution affects the optimal number of winners in rank-number tournaments. Drugov *et al.* (2018) 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.

Although the theoretical literature shows that the shape of random shocks is unrelated to equilibrium effort under optimal contracts, the empirical literature demonstrates that previous random sequential events can significantly influence subjects' decisions. Players sometimes predict that "the random sequences will exhibit excessive persistence" (Rabin & Vayanos (2010)). Such misperception is termed "hot hand belief"[6] (Gilovich *et al.* (1985)). For a literature review of hot hand belief, see Bar-Eli *et al.* (2006). In contrast, players sometimes misperceive that random sequences should exhibit systematic reversals. This phenomenon is referred to as the "gamblers' fallacy" (Tune (1964)). In practice, there is significant individual heterogeneity in biased beliefs, and it has been extensively verified in empirical studies[7] (Croson & Sundali (2005); Sundali & Croson (2006); Guryan & Kearney (2008)) and experimental studies (Ayton & Fischer (2004); Huber *et al.* (2010)). For comparisons of hot hand belief and gamblers' fallacy, see Ayton & Fischer (2004) and Oskarsson *et al.* (2009).

List *et al.* (2020) is the only experimental study that examines how distribution of random shocks impacts rank-order tournaments. They report 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

[6] In some studies, the authors also use "hot outcome" to describe the incorrect belief in positive autocorrelation of a non-autocorrelated random sequence (e.g. Sundali & Croson (2006)).

[7] Consistent with previous studies, both "gamblers' fallacy" and "hot hand belief" are observed in our work. In particular, tournament winners' behavior is more coincide with the "hot hand belief" and losers' behavior is more coincide with the "gamblers' fallacy".

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 & 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. 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 & Heywood (1989) argue 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) provide 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.

Our research most closely tracks Dutcher *et al.* (2015), which used a laboratory experiment to compare effort exertion under optimal principal-agent contracts with different tournament structures. Another important reference is Akerlof & Holden (2012), which provided theoretical analysis on how agents' effort choices in tournaments depend on the probability distribution of random shocks.

3 The Model

We model an environment with optimal principal-agent contracts, as in Lazear & Rosen (1981) and Dutcher *et al.* (2015). There are $n \geq 2$ identical risk-neutral subjects. Each subject participates in the tournaments by exerting effort $e_i > 0$.[8] 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

[8] This assumption is same as the one that stated in Dutcher *et al.* (2015).

greatest, and w_2 be the prize for the remaining subjects, where $w_1 > w_2$. The expected payoffs for subject i can be written as:

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

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:

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

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, let v_2 be the prize for the subject whose output is least, and let v_1 be the prize for the remaining subjects. The expected payoffs for subject i can be written as:

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

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

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

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 & Holden (2012), β_i equals:

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

where $F(.)$ and $f(.)$ are the cumulative distribution function and probability density function for the random shock, ε. Specifically, when $i = 1$,

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

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

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

When $i = n$,

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

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

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

As in Lazear & 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:

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

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

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

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

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

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

To conclude the model, for winner tournaments we have:

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

For the loser tournament, we have:

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

We can derive that, under the optimal principal-agent contracts, we have $c'(e^*) = c'(\bar{e}) = 1$. 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:

$$w_1 = e^* + \frac{n-1}{n\beta_1} \qquad w_2 = e^* - \frac{1}{n\beta_1} \tag{14}$$

$$v_1 = \bar{e} + \frac{1}{n\left|\beta_n\right|} \qquad v_2 = \bar{e} - \frac{n-1}{n\left|\beta_n\right|} \tag{15}$$

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:

$$\varepsilon_1 = 100 \times \left[\gamma_1 - E\left(\gamma_1\right)\right] \tag{16}$$

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

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:

$$\varepsilon_2 = 100 \times \left[\gamma_2 - E\left(\gamma_2\right)\right] \tag{17}$$

where $\gamma_2 \sim Beta(4, 2)$. Figure 1 depicts the probability density function (pdf) of γ_2.

4.1.2 Parameters of cost function

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

$$e^* = \bar{e} = 100 * \left[A - \left(rc\right)^{\frac{1}{r+1}}\right] \tag{18}$$

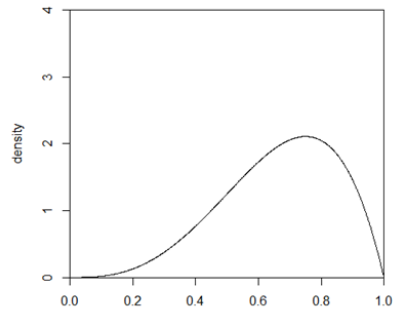


Figure 1: Probability density function of γ_2

Treatment	n	c	A	r	Prizes		e*	π
aymm_ winner	3	482.3	1.1	1.3	$w_1 = 11850$	$w_2 = 6075$	80	6360
symm_ winner	3	482.3	1.1	1.3	$w_1 = 14667$	$w_2 = 4667$	80	6360
asym_ loser	3	482.3	1.1	1.3	$v_1 = 10310$	$v_2 = 3380$	80	6360
symm_ loser	3	482.3	1.1	1.3	$v_1 = 11330$	$v_2 = 1330$	80	6360

Table 1: Treatments and parameters of experiments

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[9].

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^*. Figure 2 shows the values of $\pi(e|e^*)$ under different levels of e, which confirms that $e^* = 80$ is the pure strategy Nash equilibrium.

4.2.2 Quantal response equilibrium

Due to the relatively flat payoff functions in winner tournaments, the "flat maximum" problem may occur (Drago & Heywood (1989)). Therefore, we calculate the quantal response equilibrium (QRE) prediction (McKelvey & Palfrey (1995)), taking subjects' off-equilibrium

[9] 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.

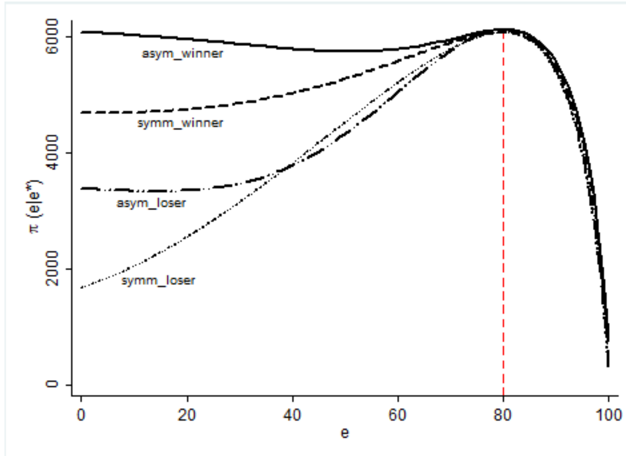


Figure 2: Expected payoffs of subject's efforts, $\pi\left(e|e^{*}\right)$

behavior into consideration. Intuitively, if subjects face flatter payoff function, they will receive less "punishment" if they deviate from equilibrium. Thus, the QRE expected effort in *asym_ winner* should be smaller than in *symm_ winner*, and the QRE expected effort in *asym_ loser* should be smaller than in *symm_ loser*. Figure 3 shows the QRE distributions of effort using the noise parameter $\lambda = 2$ [10] in winner and loser tournaments. The expected QRE efforts, in the winner tournaments, are ranked as: 50.43 in *asym_ winner* and 53.07 in *symm_ winner* ; in the loser tournaments, they are ranked as: 52.34 in *asym_ loser* and 53.82 in *symm_ loser*[11].

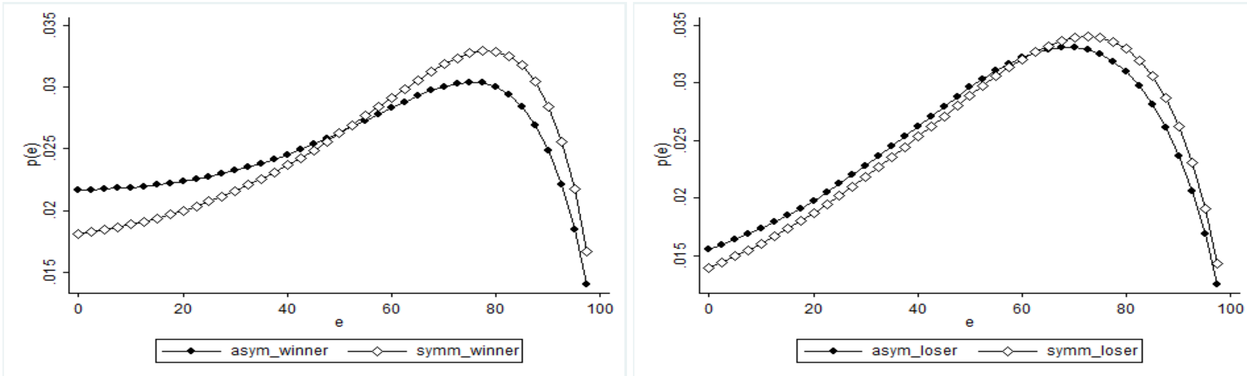
4.3 Hypotheses

Our experiment investigates how shock distributions and tournament structures affect effort. Using the QRE predictions as benchmarks[12], we calculate that average effort in

[10] In our study, we focus on comparing the "relative ranking" of expected QRE between *asym_ winner* (*asym_ loser*) and *symm_ winner* (*symm_ loser*) treatments, rather than finding the noise parameter λ that best fits our experimental data. Such ordinal relations are still valid when λ takes another value (e.g. 0.2 or 0.02). For the literature on exploring the optimal λ in contests, see Brünner (2020), Lim *et al.* (2014) and Sheremeta (2011).

[11] We can find that, the expected payoff functions in *asym_ winner* and *asym_ loser* treatments are in a "U" shape. This means that subjects receive less "punishment" if they deviate from equilibrium further. Therefore, the QRE expected efforts in asymmetric shock treatments are lower than symmetric shock treatments.

[12] 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, which makes QRE expected efforts better predictors.



(a) winner tournaments

(b) loser tournaments

Figure 3: QRE distributions of efforts in (a) winner tournaments and (b) loser tournaments

asymmetric shock treatments is lower than in treatments with symmetric shocks. This is summarized in 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 less than in the symm_loser treatment.*

One common finding in the contest literature is that previous results affect subjects' current effort. Various reasons contribute to this phenomenon. For example, it may be due to strategic momentum (Mago *et al.* (2013)) and preferences of status seeking (Mago *et al.* (2016), Gill *et al.* (2018)). Our interest is in whether different shock distributions lead to different reactions. As in Tversky & Kahneman (1974), the salience affects the retrievability of instances, thereby affecting subjects' beliefs about the likelihood of future events.[13] In our study, subjects in asymmetric shock treatment know that they have a chance of facing extremely negative shocks, meaning negative realizations are more salient. Consequently, they exaggerate the effect of preceding negative shocks and change their effort to a greater extent. This leads to our third hypothesis:

Hypothesis 3. *After receiving a negative shock in the previous round, in relation to the symmetric shock treatment, subjects facing asymmetric shocks exhibit greater change in the magnitude of their effort.*

[13] Such heuristic mistake is referred as "availability bias".

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[14] 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[15] 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, the computer drew random numbers: depending on the treatments, these random numbers could follow a symmetric distribution or asymmetric distribution, independently for each member of the group. Each 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, while the others won a lower prize w_2. In *symm_loser* and *asym_loser*, the subject with the lowest total number in each group received the bottom prize v_2, while the others received a higher prize v_1. All 20 rounds followed the same procedure mentioned above.

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

[14]See Appendix A in details
[15]See Appendix B in details

5 Results

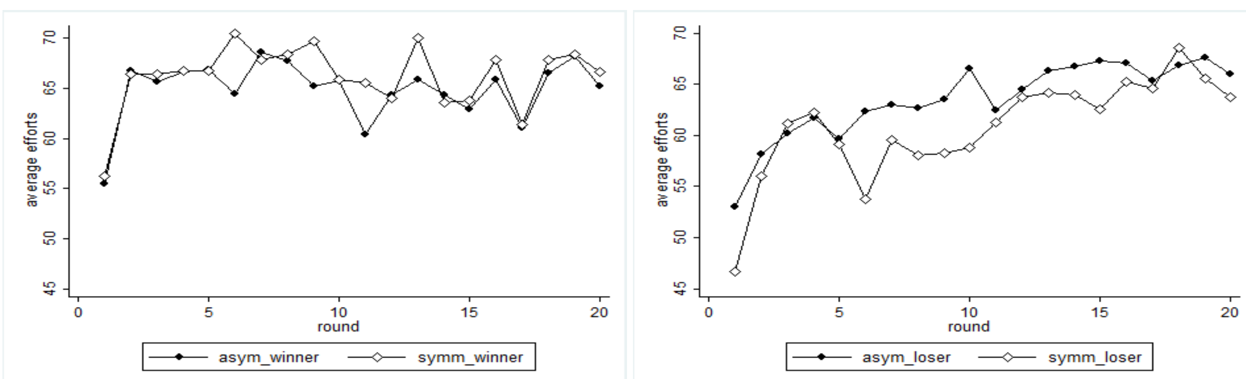
5.1 Overview of the experiments

The experiments were programmed in z-Tree (Fischbacher (2007)). We conducted all experiments at George Mason University, from June 2018 to October 2018. 192 undergraduate students participated in our experiments (54 subjects in *asym_winner*; 42 subjects in *symm_winner*; 51 subjects in *asym_loser*; 45 subjects in *symm_loser*). We conducted 16 sessions with four sessions in each treatment. The experiments lasted for about an hour and a half. Subjects could earn \$21.64 (including the \$5 show-up fees) on average.

We drop the first five rounds from our analysis, to ensure participants had sufficient experience with the interface and making decisions. Thus, all statistical tests use only data from rounds 6-20, unless indicated otherwise[16].

5.2 Average efforts

The average efforts exerted by subjects in the four treatments are shown in Figure 4.



(a) winner tournaments

(b) loser tournaments

Figure 4: Average efforts in (a) winner tournaments and (b) loser tournaments

We can see that effort provision tends to converge over time. Within treatments, subjects in all four conditions overbid in relation to QRE predictions on average[17] (Wald test, p-value < 0.001 in all four treatments). There is little difference for the average effort provision

[16] From our experimental data, if use all 20-round observations, we still have the same results as below. The reason why we delete the first five rounds, is because from Figure 4, we can see subjects' choices fluctuated a lot at the very beginning, which demonstrated they were learning at the start of our experiments.

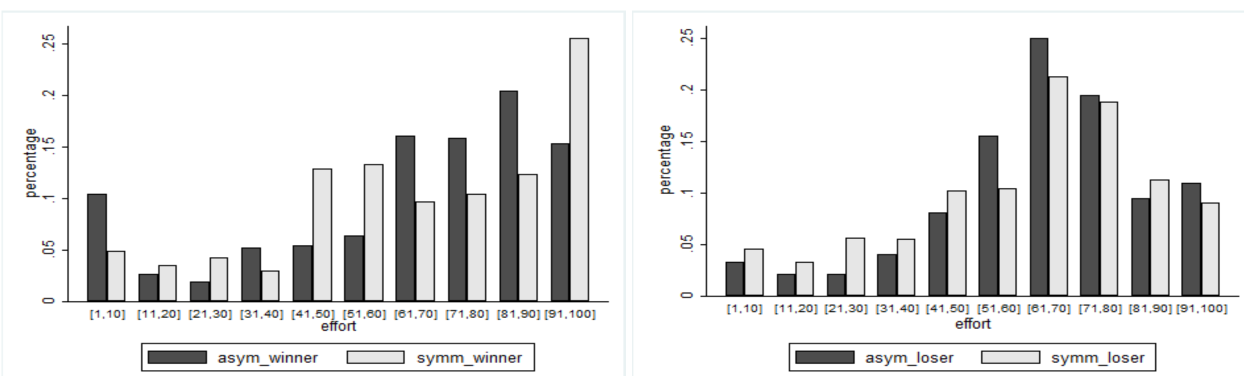
[17] If we use the pure-strategy Nash equilibrium as theoretical prediction benchmark, we find that all four treatments are underbid relative to Nash equilibrium predictions, which is consistent with the results from Dutcher *et al.* (2015).

between *symm_ winner* and *asym_ winner* (Wald test, p-value = 0.597), as well as between *symm_ loser* and *asym_ loser* (Wald test, p-value = 0.519). Table 2 shows the estimations of the panel regression models where individual subjects represent the random effects, and the standard errors are clustered at the session level. Therefore, we reject Hypothesis 1 and Hypothesis 2. Our first and second results are as follows.

Result 1. *Unlike QRE predictions, we find no statistically significant differences in effort exertion between the asym_ winner and symm_ winner treatments.*

Result 2. *Unlike QRE predictions, we find no statistically significant differences in effort exertion between the asym_ loser and symm_ loser treatments.*

Figure 5 shows the histograms of effort exertion in the different treatments. Although there is little difference in the effort provision on average between treatments, we observe substantial variance in individual behavior: In winner tournaments, subjects in *asym_ winner* are more likely to exert excessively low effort and less likely to exert excessively high effort when comparing with those in *symm_ winner*. Many subjects exerted efforts between 1-10 and 90-100 in the winner tournaments, which verifies the "bifurcation" phenomenon as in Dutcher *et al.* (2015). When analyzing the loser tournaments, unlike the winner tournaments, subjects in *asym_ loser* are less likely to exert excessively low effort and more likely to exert excessively high effort when comparing with those in *symm_ loser*. Moreover, the "bifurcation" is less obvious, as most subjects exerted effort between 51-80 in loser tournaments.



(a) winner tournaments

(b) loser tournaments

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

	(1) winner tournaments	(2) loser tournaments
Asym	-1.653	3.074
(1 if random shocks are asymmetric)	(3.129)	(4.763)
Period	$-.123$	$.525^{***}$
	(.162)	(.104)
Constant	68.37^{***}	55.294^{***}
	(1.225)	(3.42)
Observations	1440	1440
Clusters	8	8

Table 2: Panel estimation testing H1 and H2. The dependent variables are the effort exerted by subjects in (1) winner tournaments and (2) loser tournaments. The clustered standard errors are in parentheses. *, **, *** denotes statistical significance at the 10%, 5%, 1% level.

5.3 Winner tournaments

5.3.1 Average efforts for winners

We find no significant difference in the average effort exerted by the subjects in the two winner tournaments. However, from Figure 5, there is heterogeneity between subjects in winner tournaments. Therefore, we classify subjects in winner tournaments into various groups and compare their behaviors within the same group.

We refer to the subject who won the tournaments more than seven times as "winner," and others as "non-winner"[18]. To test for differences in winners' behavior in the *asym_ winner* and *symm_ winner* treatments, our first step is to calculate the average efforts exerted by winners in each round. The results are shown in Figure 6.

We find that, on average, winners exerted 86.22 efforts in *asym_ winner*, and 88.86 in *symm_ winner*. Tournament winners overbid in relation to QRE predictions in both treatments (Wald test, p-value < 0.001 in both treatments). Contrary to the ordinal relation in QRE predictions, winners in *asym_ winner* did not exert significantly less effort than those in *symm_ winner* (Wald test, p-value $= 0.519$).

In the following sections, we investigate why, in relation to the QRE predictions, winners in *asym_ winner* overbid more than those in the *symm_ winner* treatment.

[18]There are 15 rounds in total from round 6-20. On average, each ex-ante identical subject could win 15/3 = 5 times. However, unlike what theory predicted, there are quite amounts of subjects (33.3% in *asym_ winner* and 23.8% in *symm_ winner*) who won the tournaments significantly more than 5 times. Therefore, we refer these subjects as "winner".

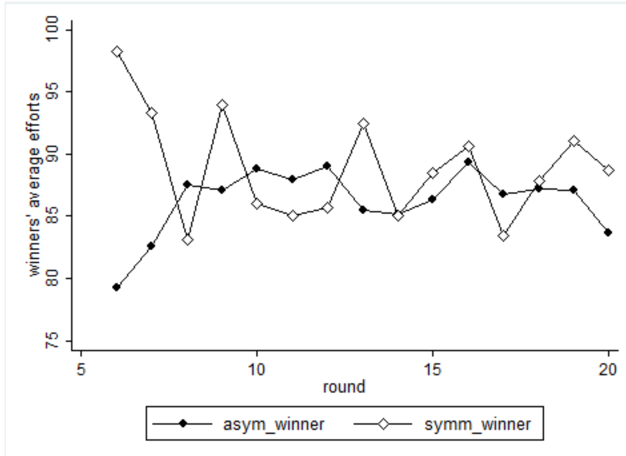


Figure 6: Average efforts exerted by winners in winner tournaments

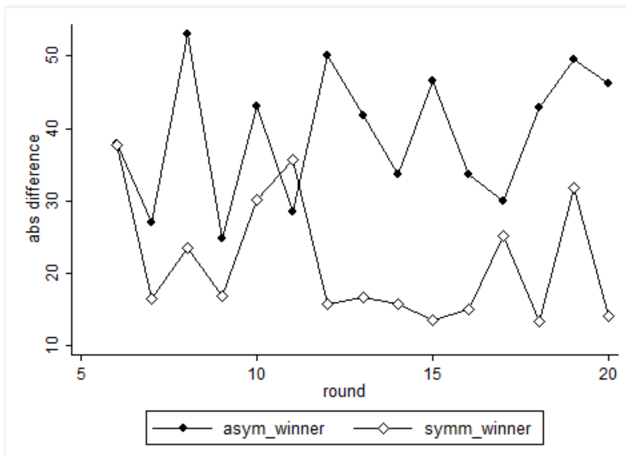


Figure 7: Average absolute difference between winners' efforts and their best response

5.3.2 Best response for winners

We find that neither Nash equilibrium nor QRE predict winners' decisions in the experiments. We next investigate whether winners were empirically best responding. We calculate winners' best response given their group members' choices and then take the absolute difference between the efforts and the best response. The average absolute differences are shown in Figure 7.

We find that winners were not best responding in either treatment. Moreover, the differences in *asym_winner* are significantly greater than those in *symm_winner*. To obtain more robust results, we conduct an individual random effect regression analysis where the dependent variable is the absolute difference between winners' efforts and their best responses.

The results are reported in Table 3. The distribution of random shocks had a significant effect on the high deviation of winners' best responses. Winners in *asym_ winner* did not best respond as well as their counterparts.

Asym	17.839***	15.156**
(1 if random shocks are asymmetric)	(7.507)	(6.497)
Male		10.941***
		(3.810)
Risk aversion		−0.140
		(1.306)
Loss aversion		0.975
		(1.524)
Constant	21.837***	14.794***
	(3.122)	(7.139)
Observations	420	420
Clusters	8	8

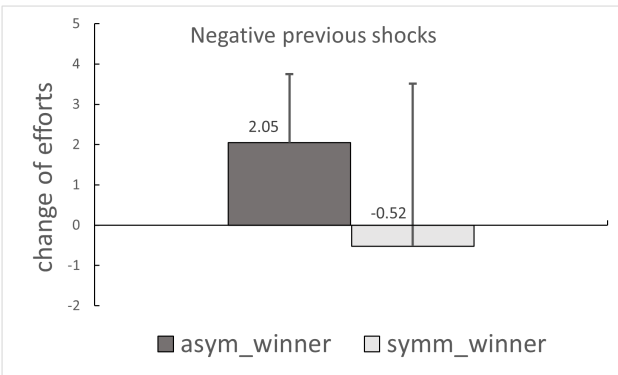
Table 3: Individual random effect panel regression results with standard errors clustered at the session level, using observations from rounds 6-20 and allowing round t as the time variable. The dependent variable is the absolute difference between winners' effort exertions and their best responses. Risk aversion is the number of risky choices subjects made in risk aversion task; Loss aversion is 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.

5.3.3 Winners' overactions to negative shocks

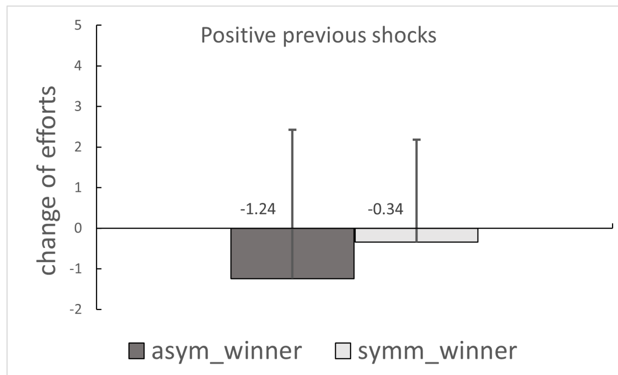
As shown in Dutcher *et al.* (2015) and Gill *et al.* (2018), the previous results affected winners' current decisions in rank order tournaments. In our experimental setting, the only difference between *asym_ winner* and *symm_ winner* was the distribution of random shocks. Specifically, in *asym_ winner*, subjects knew they may have a chance to receive extremely negative shocks. Therefore, it is natural for us to investigate whether the previous shock realizations contributed to the various overbidding behaviors for winners in different winner tournaments.

We calculate the average change in efforts for winners after receiving negative (positive) shocks in the immediately preceding round, respectively. We find that, when the immediately preceding random shocks were positive, the average change in winners' efforts was

−1.24 in *asym_ winner* and −0.34 in *symm_ winner*. However, when the immediately preceding random shocks were negative, the average change in winners' effort became 2.05 in *asym_ winner* and −0.52 in the *symm_ winner* treatment. Figure 8 compares the change in effort between positive and negative preceding shocks. Table 4 also provides regression results confirming that winners in *asym_ winner* had stronger reactions to previous shocks (Wald test, p-value = 0.024). Consequently, we fail to reject Hypothesis 3 with respect to winner behavior.



(a) negative previous shocks



(b) positive previous shocks

Figure 8: Average change in effort for winners after (a) negative shocks and (b) positive shocks in previous round. The error bar represents 0.2 times the standard deviation of the observations.

	(1)		(2)	
	Winners		Non-winners	
Asym× Negative	3.463**	3.302**	3.209	3.153
	(1.460)	(1.461)	(2.874)	(2.933)
Negative	−0.176	0.016	−0.954	−0.945
	(0.673)	(0.745)	(2.810)	(2.851)
Asym	−0.890	−1.912	−1.899	−1.714
	(1.017)	(1.388)	(1.559)	(1.663)
Magnitude of shocks		−0.099		0.016
		(0.077)		(0.049)
Male		−0.124		−0.242
		(0.232)		(0.748)
Risk aversion		−0.126***		−0.093
		(0.036)		(0.125)
Loss aversion		−0.153		0.007
		(0.094)		(0.323)
Constant	−0.346	3.264	0.616	0.803
	(0.593)	(2.270)	(1.528)	(2.317)
Observations	420	420	1020	1020
Clusters	8	8	8	8

Table 4: Individual random effect panel regression with standard errors clustered at the session level, using observations from rounds 6-20 and allowing round t as the time variable. The dependent variable is the change in efforts for (1) winners and (2) non-winners in winner tournaments. Magnitude of shocks is the absolute value of random shocks winners faced in the immediately preceding round; Asym equals 1 if the random shocks are asymmetrically distributed in treatments, and 0 if the random shocks are symmetrically distributed; Negative equals 1 if the immediately previous shocks are negative, and 0 if the previous shocks are positive; Risk aversion is the number of risky choices subjects made in the risk aversion task; Loss aversion is 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.

Why did winners in *asym_ winner* have stronger reactions to previous shocks? We hypothesized that winners in *asym_ winner* knew they had a chance of facing extremely negative shocks; therefore, they were more likely to fall into hot hand belief. Specifically, when suffering negative shocks in previous rounds, winners in *asym_ winner* were more likely to hold an incorrect belief in positive autocorrelation of the independent random shocks, believing they would face negative shocks in the following rounds. As a result, they were deterred and exerted greater effort to win the tournament. This is consistent with "elite competition." The reason is that athletes know it is possible for them to face extremely negative shocks in competitions. Once this occurs, they may amplify their failures and exert greater effort to win the gold medal.

5.3.4 Non-winners' behaviors in winner tournaments

We next investigate non-winners' behavior, to determine whether realizing random shocks also contributes to their various behavioral patterns. We calculate the average efforts non-winners exerted in *asym_ winner* and *symm_ winner* treatments, and find that non-winners in *asym_ winner* did not exert less effort than those in *symm_ winner* (Wald test, p-value = 0.312)[19]. Next, we investigate non-winners' reactions to random shocks. We find that, no matter what the previous shocks looked like, non-winners did not exhibit a significant difference in effort exertion in *asym_ winner* and *symm_ winner* (Wald test, p-value = 0.282). The regression analysis set forth in Table 4 further confirms this finding. Our third result is thus as follows.

Result 3. *In winner tournaments, winners have stronger reactions to negative shocks in asym_ winner than symm_ winner. This finding is exclusive to tournament winners. We observe no significant effort response to shocks among non-winners in both treatments.*

5.4 Loser tournaments

5.4.1 Losers' behavior in loser tournaments

Similar to winner tournaments, we classify subjects in loser tournaments into different groups, and compare their behaviors within the same group. We refer to the subject who lost the tournaments more than seven times as "loser," and others as "non-loser"[20].

[19] On average, non-winners in *asym_ winner* exerted 54.56 effort and in *symm_ winner* exerted 59.87 effort.

[20] There are 15 rounds in total from round 6-20 in loser tournaments. On average, each ex-ante identical subject could lose $15/3 = 5$ times. However, unlike what theory predicted, there are large numbers of subjects (27.4% in *asym_ loser*, and 26.67% in *symm_ loser*) who lost the tournaments significantly more than 5 times. We call these subjects who lost the tournaments more frequently "loser."

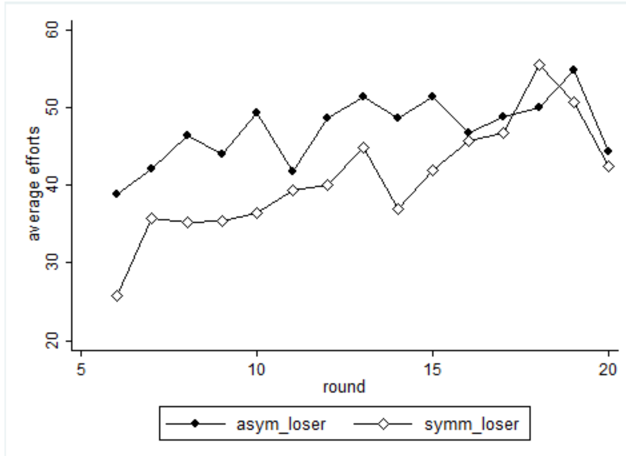
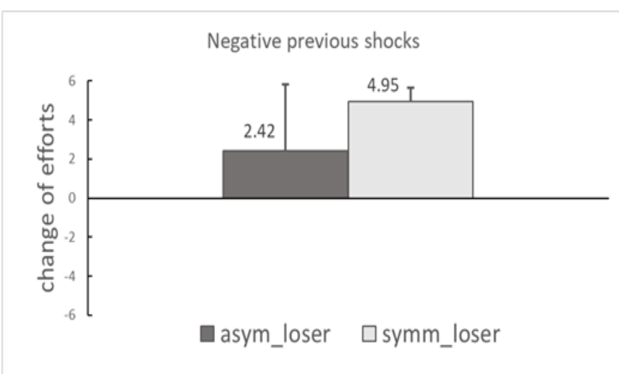


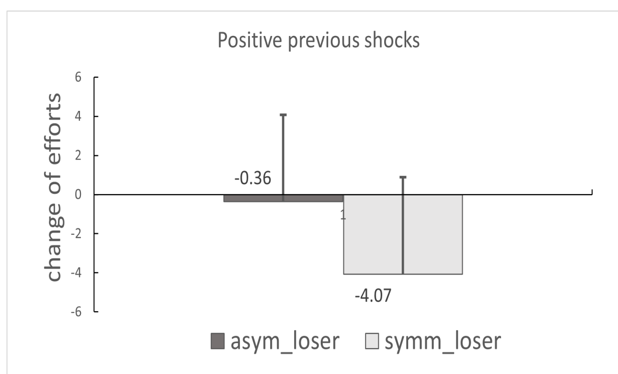
Figure 9: Average effort exerted by losers in loser tournaments

We first calculate the average effort exerted by losers in each round. The results are shown in Figure 9. We find that, on average, losers in *asym_ loser* exerted 47.32 efforts and losers in *symm_ loser* exerted 40.73 efforts. Both are below the QRE predictions (Wald test, p-value = 0.096 in *asym_ loser* and p-value = 0.001 in *symm_ loser*). Unlike the ordinal relation predicted by QRE, tournament losers in *asym_ loser* exerted no less effort than those in *symm_ loser*. Statistical tests verify this result (Wald test, p-value = 0.513).

We next test whether the fact that losers in *asym_ loser* exerted no less effort than losers in *symm_ loser* is due to their various reactions to different realizations of random shocks. We calculate the change in efforts for losers, when facing immediately previous negative (positive) shocks, in different treatments. The results are shown in Figure 10.



(a) negative previous shocks



(b) positive previous shocks

Figure 10: Average change in effort for losers after (a) negative shocks and (b) positive shocks in previous round. The error bar represents 0.2 times the standard deviation of the observations.

We find that, when the immediately preceding random shocks were positive, the average change in losers' efforts was -0.36 in *asym_loser* and -4.07 in *symm_loser*. When the immediately preceding random shocks were negative, the average change in losers' effort became 2.42 in *asym_loser* and 4.95 in the *symm_loser* treatment. Table 5 also provides regression results confirming that losers in *asym_loser* under-reacted to previous shocks than those in *symm_loser* (Wald test, p-value = 0.026). Therefore, we reject Hypothesis 3 with respect to loser behavior.

	(1) Non-losers		(2) Losers	
Asym× Negative	2.099	2.039	-6.235^{***}	-6.420^{**}
	(1.960)	(2.008)	(2.775)	(2.879)
Negative	0.617	0.639	9.017^{***}	8.938^{***}
	(1.560)	(1.564)	(2.314)	(2.413)
Asym	−0.786	−0.513	3.709^{***}	4.745^{**}
	(1.013)	(1.113)	(1.429)	(1.930)
Magnitude of shocks		0.029		0.076
		(0.026)		(0.082)
Male		0.142		0.020
		(0.268)		(0.243)
Risk aversion		−0.162		0.166
		(0.175)		(0.120)
Loss aversion		0.097		0.115
		(0.195)		(0.137)
Constant	−0.127	−0.441	-4.070^{***}	-7.108^{***}
	(0.830)	(1.225)	(1.186)	(2.343)
Observations	1050	1050	390	390
Clusters	8	8	8	8

Table 5: Individual random effect panel regression with standard errors clustered at the session level, using observations from rounds 6-20 and allowing round t as the time variable. The dependent variable is the change in efforts for (1) non-losers and (2) losers in loser tournaments. Magnitude of shocks is the absolute value of random shocks non-losers faced in the immediately preceding round; Asym equals 1 if the random shocks are asymmetrically distributed in treatments, and 0 if the random shocks are symmetrically distributed; Negative equals 1 if the immediately previous shocks are negative, and 0 if the previous shocks are positive; Risk aversion is the number of risky choices subjects made in the risk aversion task; Loss aversion is 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.

5.4.2 Non-losers' behavior in loser tournaments

We next investigate whether there are differences in effort between the tournament non-losers in the *asym_ loser* and *symm_ loser* treatments.

To avoid losing the loser tournaments, non-losers in *asym_ loser*, on average, exerted 72.03 efforts, while those in *symm_ loser* exerted 69.06 efforts. They were above the QRE predictions (Wald test, p-value < 0.001 in *asym_ loser* and p-value $= 0.003$ in *symm_ loser*), and non-losers in *asym_ loser* exerted no less effort than those in *symm_ loser* (Wald test, p-value $= 0.644$).

Similar to our analysis above, we now test whether the fact that non-losers in *asym_ loser* exerted significantly greater effort than non-losers in *symm_ loser* is due to their various reactions to different realizations of random shocks. We calculate the change in effort for non-losers, when facing immediately previous negative (positive) shocks, in different treatments. We do not find statistically significant difference in reactions to previous shocks among non-losers between *asym_ loser* and *symm_ loser* treatments (Wald test, p-value $= 0.310$)[21]. The regression results on Table 5 further confirm our findings.

Although non-losers in *asym_ loser* exerted no less than non-losers in *symm_ loser*, they did not exhibit significant different reactions to previous random shock realizations. Our final result is:

Result 4. *In loser tournaments, losers are less responsive to negative shocks in asym_ loser than symm_ loser. This result is exclusive to tournament losers. Among non-losers, we observe no significant effects of random shock realizations on effort decisions in either treatment.*

6 Conclusion

Rank order tournaments are ubiquitous and widely used in everyday life. As a result, they have been heavily investigated in the experimental research. However, previous empirical literature has assumed that random shocks follow a symmetric distribution. This is an important issue, especially when subjects are homogenous. Research suggest that subjects respond to realizations of random variables, even when they should not, and that these biases in behavior could impact effort decisions in tournaments. In this paper, we use experimental methods to investigate subjects' behavior under different random shock distributions.

[21] When facing immediately preceding negative shocks, on average, non-losers in *asym_ loser* exerted 1.83 more effort, while non-losers in *symm_ loser* exerted 0.49 more effort. When facing immediately previous positive shocks, non-losers in *asym_ loser* exerted 0.12 less effort, while those in *symm_ loser* exerted 0.91 less effort.

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 certain parameters that make the asymmetric distribution become unimodal and negative skewed, allowing for subjects to meet extremely negative shocks. The asymmetric-distribution shocks can better depict tournaments like "elite competition." We also provided two different tournament structures, winner tournament and loser tournament, to investigate how subjects' behaviors change when the goal is to "strive to be first" or "avoid being last."

In contrast to the theoretical predictions, subjects exerted greater effort than the QRE prediction. However, the manner in which subjects came to the average varied. In winner tournaments, unlike the ordinal relations predicted by QRE, to win the tournaments, winners in *asym_winner* exerted no less effort than those in *symm_winner*, and winners in *asym_winner* were worse at best-responding. One explanation for this irrationality is that winners in *asym_winner* were more likely to fall into hot hand belief. Namely, they knew that they had a chance to face extremely negative shocks, and thus, having suffered negative shocks in preceding rounds, were more likely to hold an incorrect belief in positive autocorrelation of the independent random shocks (i.e., believe they would face (extremely) negative shocks in the following rounds). As a result, they were deterred and exerted greater effort to win the tournament. However, in loser tournaments, although losers in *asym_loser* exerted no less effort than those in *symm_loser*, the reason is that losers in *asym_loser* were less likely to fall into such hot hand belief. Particularly, when suffering positive (negative) shocks in previous rounds, they were less likely to hold an incorrect belief in positive autocorrelation of the independent random shocks. Therefore, they did not decrease (increase) their efforts as much as those in *symm_loser*. We find statistical evidence to support these explanations.

The findings above, especially for winner tournaments, are consistent with "elite competition". The reason is that top athletes in competitions know it is possible for them to face extremely negative shocks. As a result, once they do so, they tend to exert greater effort to win the top prize. Our research provides a deeper understanding of winners' (losers') behavior in tournaments where random shocks are asymmetrically distributed.

Our study highlights the impact of negative shock realizations on future economic decision making. While we focused on contests, the behavioral economics underlying the effects we observed would seem to apply to a wide variety of situations. For example, understood as an extremely negative shock, our results suggest people may respond differently to COVID-19, and more importantly, those differences may impact whether one achieves positive economic outcomes going forward. An important avenue for future research could focus on the way people respond to significant negative shocks, and how those responses translate into life satisfaction and well-being.

A Appendix: Experimental instructions (Use *asym_ winner* as examples)

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" 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**

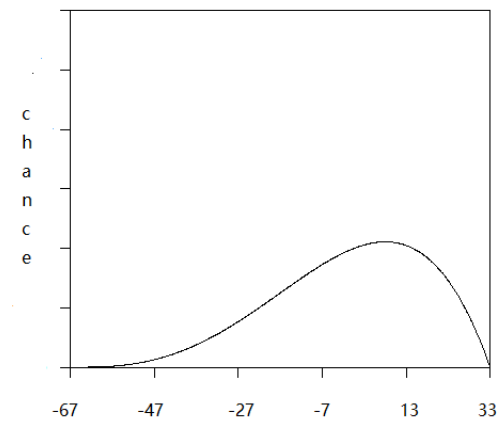


Figure A1: The chance for each number to be drawn

numbers have different chances to be drawn. The chance for each number to be drawn from this range has the shape in Figure A1 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.

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.

	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 A1: Example 1

	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 A2: Example 2

Examples:

Let's go through an example. Suppose the Table A1 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 A2:

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.

B Appendix: Examples (Use asymmetric distribution as examples)

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

-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;

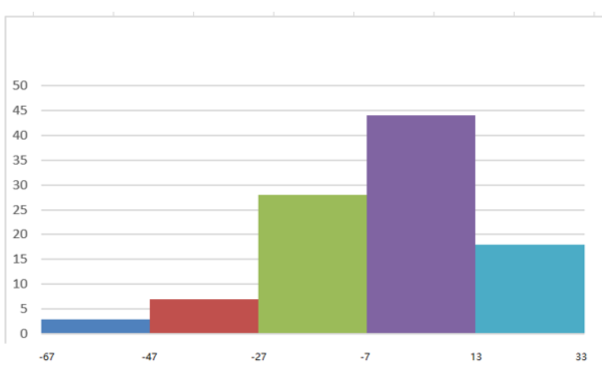
The number of random draws fall between -47 to -27: 7;

The number of random draws fall between -27 to -7:28;

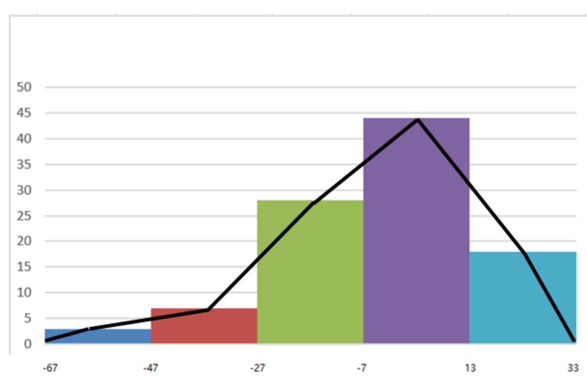
The number of random draws fall between -7 to 13:44;

The number of random draws fall between 13 to 33:18;

More intuitively, Figure B2a shows several rectangles: the height of each rectangle represents the number of draws that falls in this certain range.



(a) Figure B2a



(b) Figure B2b

If we use lines to connect the upper-middle points in each rectangle in Figure B2a, then we can get the similar shape (as shown in Figure B2b) 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?

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