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Does Unfairness Hurt Women? The Effects of Losing Unfair Competitions

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Abstract

How do men and women differ in their persistence after experiencing failure in a competitive environment? We tackle this question by combining a large online experiment (N=2,086) with machine learning. We find that when losing is unequivocally due to merit, both men and women exhibit a significant decrease in subsequent tournament entry. However, when the prior tournament is unfair, i.e., a loss is no longer necessarily based on merit, women are more discouraged than men. These results suggest that transparent meritocratic criteria may play a key role in preventing women from falling behind after experiencing a loss.

JEL-codes: C90, D91, J16, C14

Key words: Competitiveness, Gender, Fairness, Machine learning, Online experiment

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1 Introduction

Competition is a pervasive aspect of many labor market activities. While a select few may win every promotion contest and job applied for, for most of us the road to success is paved with failures. Evidence from psychology suggests that men and women may respond to failure in different ways (Ryckman & Peckham, 1987; Dweck *et al.*, 1978). If this is true, it may explain why men may persist after the latest failed job application or desk rejection (Shastry & Shurchkov, 2022), whereas women may throw in the towel. These gender differences in response to failure may in turn contribute to explaining existing disparities in the labor market.

In this paper, we conduct a pre-registered online experiment ($N = 2,086$) in which we study gender differences in persistence after an experience of failure in a competition. In particular, participants in our experiment perform in real-effort counting tasks under an initial two-person winner-takes-all tournament. After receiving feedback on the tournament outcome, participants choose between tournament pay and a safer alternative (piece rate) for their next performance. By comparing the tournament entry choices of similar performing men and women who either won or lost the initial tournament, we are able to study gender differences in the ability to deal with the experience of failure.

We compare behavior in this baseline treatment to a second treatment in which participants are informed that the prize in the *initial* tournament is sometimes randomly awarded to the inferior performer. This treatment captures an important class of applications in which tournament winners are at least partially determined by criteria that are orthogonal to performance.[1] Since such criteria violate meritocratic fairness norms (Cappelen *et al.*, 2007, Alesina & Giuliano, 2011), we term this treatment the "unfair" treatment. Importantly, participants in this treatment are not informed about whether the outcome of their specific initial tournament was determined in a merit-based or random way. Though the subsequent second tournament is always merit-based, prior experience of an unfair (i.e., not fully merit-based) tournament can still impact tournament entry, i.e. persistence, for at least three reasons. First, the outcome of an unfair tournament has less information value than losing a baseline (i.e., fair) tournament. Second, losing an

[1]Examples of criteria orthogonal to performance include quasi-random factors (such as the agreeableness of a specific reviewer in academia), as well as more systematic factors (such as quotas or cronyism in hiring).

unfair tournament may have a different discouragement effect on preferences for risk or competition. Third, unfairness may, in the spirit of motivated reasoning, be used as a convenient excuse to maintain a positive self-image ("I lost because the competition was rigged against me"). If, after losing, men update their beliefs less than women, are less discouraged by losses, or are more able to come up with excuses, we may observe a greater gender gap in this second treatment.

Our results are broadly in line with this hypothesis. In particular, conditional on performance, losing rather than winning a fair tournament strongly decreases the willingness to compete in the baseline (fair) treatment, with men and women responding in similar ways. By contrast, when the tournament is unfair, women respond more strongly to losing the competition. In line with our hypothesis, women are therefore less persistent than men after facing adversity when they know that adversity may have been the result of unfairness.

We study potential reasons why women respond more to the outcome of an unfair tournament using a third treatment in which the prior tournament is unfair, but participants receive feedback on their true performance (ability rank) and whether their performance was good enough to win the competition. This additional feedback ensures that the tournament outcome has no further information value, and unfairness can no longer be used as an excuse to justify a loss. Nevertheless, we find evidence that women (but not men) still respond to losing the competition. This suggests that losing an unfair competition has a discouragement effect on women's preferences for risk or competition—but not men's.

In addition to looking at the average effect of losing a competition, we leverage our large sample size and extensive set of demographic variables to examine heterogeneity in the effect of losing a tournament using causal forests (Athey *et al.*, 2019). This allows us to examine (i) whether the gender difference in unfair tournaments survives when controlling for a large number variables in a flexible and data-driven way using causal forests, and (ii) whether other factors different than gender are important determinants of the effect of losing a competition. Our results indicate that (i) gender indeed plays an important role in the unfair treatment but not in the baseline treatment, and that (ii) other demographics such as age, the number of male siblings, and practicing sports in adolescence also predict both tournament entry and the effect of losing a competition.

Our study relates to a large literature that has linked existing gender differences in the labor market to gender differences in psychological traits. These studies show that men tend to be more self-confident, less risk averse, more willing to compete, and less egalitarian than women, and that these differences can be linked to labor market outcomes (see, e.g., Croson & Gneezy, 2009, Niederle, 2016, Lozano *et al.*, 2023, or Markowsky & Beblo, 2022 for reviews of this literature). Most closely related to our work is Buser & Yuan (2019), who also explore gender differences in the response to losing a competition. Building upon their design, our study presents new evidence that these differences may be exacerbated in the presence of meritocratic unfairness, which provides a rationale for policy makers to foster institutions that are perceived as fair. Moreover, to the best of our knowledge, we are the first to estimate the effect of losing a competition (fair or unfair) in a large and representative online sample.

Our paper also speaks to the literature investigating the role of meritocratic fairness norms and other fairness principles (e.g., Cappelen *et al.*, 2007; Cappelen *et al.*, 2013; Cappelen *et al.*, 2022; Alesina & Giuliano, 2011). A relevant recent study is Buser *et al.* (2021a), who study preferences for entering fair and unfair competitions. We contribute to this literature by studying how the experience of meritocratic unfairness affects the tendency to persevere in the face of adversity. In so doing, we also connect to the literature on motivated beliefs (see, e.g., Ambuehl, 2021; Babcock *et al.*, 1996) by exploring whether participants selectively attribute a loss to unfair institutions.

In addition, we contribute to the growing literature estimating heterogeneous effects using machine learning methods (e.g., Athey & Wager, 2019; Athey *et al.*, 2019; Athey & Imbens, 2016). These methods have gained prominence in recent years because they have the potential to allow treatment effects to be estimated at the individual level, thereby pinning down the key drivers of treatment effects, improving predictive power, and potentially increasing external validity (Chernozhukov *et al.*, 2020). We contribute to this literature by applying these methods in the context of an experiment, allowing us to estimate treatment effects at the individual level conditional on a rich set of individual characteristics without making *ad hoc* modelling assumptions. In so doing, we also contribute to the experimental literature by showcasing how these methods can be used to investigate heterogeneous effects in the context of experiments.

The remainder of the paper is structured as follows. Section 2 describes the experimental design. Section 3 presents a brief overview of our hypotheses. Section 4 presents the main result separately for each treatment, followed by a discussion of heterogeneous effects. Section 5 concludes.

2 Experimental Design

We conducted an online experiment in which participants worked on a real-effort task for three stages (see Figure 1). Building on the seminal design of Niederle & Vesterlund (2007), participants received piece rate incentives in Stage 1, tournament incentives in Stage 2, and could choose among the two previous incentives in Stage 3. One of the three stages was randomly selected for payment. There were three between-subject treatments, which differed in the nature of the competition in Stage 2—"fair" or "unfair"—and the type of feedback provided in that stage. We will start by describing the design of our baseline treatment (which we will refer to as the "Neutral Treatment"), then lay out the differences compared with the other two treatments, followed by a description of the questionnaire and experimental procedures. All instructions can be found in Appendix E.

Neutral Treatment.– The real-effort task we used consisted of counting the number of zeros in 8x8 tables consisting of zeros (0) and ones (1). Participants had 90 seconds to solve as many tables as they could, where solving a table meant reporting the correct number of zeros in the respective table. We will refer to the number of solved tables as their "score". We deviated from the task used in most previous laboratory experiments (addition problems) to reduce the potential for cheating in the online setting, e.g., by using a calculator. The counting zeroes task has previously been used by Abeler *et al.* (2011) and Apicella *et al.* (2017), among others.

In Stage 1, participants were paid a piece rate of 0.15 pounds per table they solved correctly. In Stage 2, participants were instead remunerated according to a two-person winner-takes-all tournament. Participants were told that they would receive 0.30 pounds per table if their score exceeded the score of a random opponent who had already completed the task, and zero otherwise. Ties were broken randomly. The opponent's score was randomly selected from the score distribution of participants in Apicella *et al.* (2017). In Stage 3, participants made a choice whether to apply piece rate or tournament pay to their performance. If they chose

Stage 1: Piece Rate

- Solve tables for 90 seconds with Piece Rate incentives (£0.15 per table)
- Feedback: "You scored ... correct answers."

Stage 2: Tournament

- Prior belief elicitation: tournament rank in Stage 2 (£0.50-£0.02*guessing error)
- Solve tables for 90 seconds with Tournament incentives (£0.30 per table for winners, 0 for losers)
    - ⋆ *Neutral Treatment.*– Best performer wins, ties broken randomly
    - ⋆ *Unfair/Feedback Treatment.*– Best performer wins 75% of the time, worst performer wins 25% of the time, ties broken randomly
- Feedback: "You scored ... correct answers. You won/lost in the tournament in Stage 2."
    - ⋆ *Feedback Treatment:* Additional feedback consisting of performance rank relative to the comparison sample + information on whether their score exceeded the score of the opponent and they (un)deservedly won/lost the tournament.
- *Neutral/Unfair Treatment.*– Posterior belief elicitation: tournament rank in Stage 2 (£0.50-£0.02*guessing error)

Stage 3: Choice

- Choose between Piece Rate and Tournament incentives
- Solve tables for 90 seconds under chosen incentive
- Feedback: "You scored ... correct answers." (if piece rate was chosen).
- Feedback: "You scored ... correct answers. You won/lost in the tournament in Stage 3" (if tournament was chosen).

Questionnaire

- Demographics + preferences for risk, competition, and fairness

Payment Screen

- One Stage randomly selected for payment

Figure 1: Overview of the Experiment

the tournament, their opponent's score was once again randomly selected from the same score distribution of prior participants.

Apart from the task, our design differed from Niederle & Vesterlund (2007) in two main ways. First, we informed participants after Stage 2 whether they won or lost the tournament. This difference is crucial to study the effect of failure (losing a competition) on tournament entry in Stage 3. Second, we included two incentivized belief elicitation tasks in Stage 2, one just before the start of the real-effort task and one at the end (after receiving information on whether they won or lost the tournament). In both elicitation tasks, we asked participants to estimate their rank compared to 100 prior participants in Stage 2. To keep things simple, participants were paid according to a linear scoring rule that awarded them a base payment of 0.50 pounds minus 0.02 pounds times the absolute difference between the true rank and the stated (guessed) rank, with a minimum of zero. In case of ties, participants were assigned their expected rank.

Unfair Treatment.– Our goal in designing our second treatment was to introduce unfairness in the sense that the winner would no longer be determined in a fully meritocratic way. Previous research has implemented unfairness using quotas, performance boosts and other instruments to move away from a pure meritocracy, typically to the benefit of women (e.g., Balafoutas & Sutter, 2012; Niederle *et al.*, 2013; Buser *et al.*, 2021a). We instead use an arguably more general approach in which distortions away from meritocracy are generated by a random process rather than being linked to gender or other specific demographic characteristics.

Hence, the only difference between this treatment and the Neutral Treatment lies in the way the winner was determined in Stage 2. In contrast to the Neutral Treatment, where the best performer would always win the tournament, participants in the Unfair treatment were informed that there was a 75% chance that the best performer would win the tournament. In the remaining 25% of cases, the inferior performer would win instead.

It is important to note that this change only applied to Stage 2. In Stage 3, the tournament (if chosen) was still a fair (neutral) tournament, where the best performer always won. Prior to Stage 3, participants in all treatments were explicitly informed that the best performer would always win in the tournament (if chosen). This design feature allows us to attribute differences in tournament entry in Stage 3 to the experience of winning or losing a prior competition, as opposed to the willingness to enter fair versus unfair competitions.

Feedback Treatment.– This treatment is identical to the Unfair Treatment, except that participants received two additional items of feedback at the end of Stage 2. First, we informed participants about their true rank in Stage 2 relative to the comparison sample of 100 participants. In case of ties, participants were assigned their expected rank. Second, we told participants whether their score was higher than their opponent's and whether they deservedly (75% of the time) or undeservedly (25% of the time) won or lost the tournament. This treatment therefore gives participants perfect information about both the nature of the competition and their ability rank. The only other change was that we removed the belief elicitation task at the end of Stage 2, because participants knew their exact rank.

The Questionnaire.– The final part of the experiment consisted of a questionnaire. Part of the purpose of the questionnaire was to collect a large number of background characteristics to allow us to investigate heterogeneous treatment effects. Individual characteristics included about 50 variables describing (i) personal information such as age, educational attainment level, ethnicity, employment status, and type of job; (ii) family background variables such as the number, gender, and age of siblings, whether the person lived together with the siblings, the number and age of their own children, whether children go to school or follow homeschooling; and (iii) spare time activities such as whether individuals participated in any official sport competition regularly during adolescence and the type of sport (individual vs. team). In addition, we elicited participants' risk preferences as well as their self-reported competitiveness and fairness perceptions. A full description of the included questions as well as detailed information on the selected measures of risk attitudes, competitiveness, and perception of unfairness can be found in Table in 4 the Appendix.

Procedures.– The experiment was programmed in Qualtrics and run on the platform Prolific in May and June 2021. To ensure high quality responses, we only invited native English speakers based in the UK or the US who had taken part in at least 10 prior surveys on Prolific, and whose survey responses were accepted at least 95% of the time. Further, we used a captcha test to filter out non-human users. To filter out participants who were not paying attention, we included a set of comprehension questions after the Stage 1 instructions and two attention checks during the final questionnaire (see Appendix E).

The median time to complete the study was 13 minutes and 35 seconds. Participants who completed the study received a participation fee of £1.50 and a bonus payment which depended on the decisions they made in the experiment and their task performance. They received feedback about their earnings after they completed the questionnaire. The median payment (show up fee plus earnings from the tasks) was £2.10.

3 Hypotheses

How does the outcome of a prior competition affect one's subsequent willingness to compete? And how does this effect depend on whether the prior competition was fair or unfair, and on gender? To answer these questions, let us start by considering an expected utility maximizing agent, who will choose the tournament in Stage 3 if:

$$p_i^s(W_3)u_i(0.30x_i) > u_i(0.15x_i) \tag{1}$$

Here, x_i is the agent's performance on the task, and $p_i^s(W_3)$ is agent's i subjective probability of winning the tournament in Stage 3. Intuitively, the agent will choose to enter the tournament if she is sufficiently optimistic about her chances of winning (as captured by $p_i^s(W_3)$) and not too risk averse (as captured by the curvature of $u_i(x_i)$). Note that we assume that $u_i(0) = 0$ to simplify the notation. Our framework can be easily extended to incorporate other preference parameters (such as competitiveness) into the utility function.

Losing a tournament may reduce subsequent willingness to compete through both channels (beliefs and preferences). First, in terms of *beliefs*, participants should update their subjective win probability $p_i^s(W_3)$ based on the outcome of Stage 2. Intuitively, losing (winning) the Stage 2 tournament is a negative (positive) signal of ability that should make participants more pessimistic (optimistic) about their win chances in Stage 3. We formalize this intuition further in Appendix A. Second, the experience of winning or losing a prior tournament may directly affect *preferences* ($u(x_i)$). In particular, losing a competition may result in a "discouragement effect" whereby participants become less interested in entering a subsequent competition, because, e.g., they become more risk averse or become averse to further disappointments (Gill & Prowse, 2012). Conditional on performance, both channels imply that we should expect Stage 2 losers to be significantly less likely to compete in Stage 3 than winners in all treatments.

However, we expect the difference between losers and winners to be smaller when unfairness is introduced. In the Unfair Treatment, there is a 25% chance that the inferior performer wins (and the superior performer loses) the tournament in Stage 2. This implies that the outcome of Stage 2 is a weaker (only about half as informative) signal of ability relative to the Neutral Treatment, as we show more formally in Appendix A. As a result, we predict that the difference in Stage 3 tournament entry rates between Stage 2 winners and losers will be smaller in the Unfair Treatment than in the Neutral Treatment. Beyond the rational Bayesian argument, participants may also be able to use unfairness as an excuse to justify a loss ("I lost because the competition was rigged against me"), while still attributing a win to their own ability ("I won because I am good at the task"). This motivated reasoning argument implies that winners compete at similar rates in both treatments but losers compete at higher rates in the Unfair treatment. Both the rational Bayesian argument and the motivated reasoning argument therefore predict a smaller difference between winner and loser entry rates in the Unfair than in the Neutral treatment.

When it comes to gender, we predict that moving from the Neutral Treatment to the Unfair Treatment will increase the size of the gender gap for two reasons. First, previous research suggests that men are more likely to attribute failure to external factors such as bad luck (Dweck *et al.*, 1978; Shastry *et al.*, 2020; Thaler, 2021). That is, men are better able to come up with excuses to explain bad outcomes. Unfairness increases the scope for such excuses, which should make men even less responsive to losing. Second, a series of studies present evidence that women are more concerned about unfairness and reducing inequality (e.g., Andreoni & Vesterlund, 2001, Fehr *et al.*, 2006, Ranehill & Weber, 2022). This suggests that women may experience a greater discouragement effect after an unfair competition, potentially increasing their response to a loss. Overall, if men respond less and women respond more to losing, we should then observe a larger gender gap in the Unfair Treatment than in the Neutral Treatment.

Hence, our main hypotheses are the following:

1. *The Effect of Losing:* Stage 2 losers are less likely to compete in Stage 3 than Stage 2 winners.

2. *Unfairness:* The effect of losing will be smaller in the Unfair Treatment than in the Neutral Treatment.

3. *Gender and Unfairness:* The gender gap in the effect of losing will be larger in the Unfair Treatment than in the Neutral Treatment.

We can use the final treatment (Feedback Treatment) to study the mechanisms behind any (gender) differences we may observe across the other two treatments. In particular, conditional on knowing one's own ability rank in Stage 2, winning or losing is a random event that no longer has any predictive power for success in Stage 3. Conditional on performance, any residual gender gap in response to losing can therefore be attributed to the preference channel.

4 Results

In this section, we start with presenting descriptive statistics on our sample. We then examine the effect of losing a competition on subsequent tournament entry in a fair competition (Neutral Treatment), followed by a discussion of how this effect changes in an unfair competition (Unfair Treatment). Along with looking at gender differences in both treatments, this allows us to test our three main hypotheses. Subsequently, we use data from the Feedback Treatment to analyze whether any differences between the two treatments and between gender are driven by differences in preferences or beliefs. Finally, we use machine learning techniques to further study heterogeneity in the effect of losing a competition.

4.1 Descriptives

Table 1 presents choices and outcomes from our experiment, sorted by gender. Women scored slightly higher in Stage 1 (solving on average 3.4 versus 3.2 tables correctly) and managed to win more often than men in Stage 2 (58% of women do so, versus 52% of men). Despite these differences, and in line with previous work, we find that men were significantly more likely to compete, namely, 45% of men chose the tournament scheme in Stage 3 across all treatments, versus 40% of women.[2] Also in line with previous research, men were more confident about their

[2] While significant, the gender gap is smaller than the one typically found in the literature (see, e.g., Table A11 in Van Veldhuizen, 2022, where the average gap is 24 percentage points). Possible

task ability than women (as evidenced by their lower post-feedback rank). Men also stated to be more willing to take risks and like competitive environments more in all elicited measures. Further, we see that men experienced less unfair treatment than women in the past, and would be less disappointed by unfair treatments to others.

Men and women are similar in their demographics and family characteristics. Participants are on average 35 years old and have one older brother and one older sister. About 36% of men and 31% of women have children, mostly in school age. Regarding the labor market, both men and women work, and work rather full time than part time. Yet, as to be expected, women work part time more often than men. In terms of education outcomes, most participants hold a Bachelors degree or higher, with men appearing to be slightly more educated overall. The ethnicity of participants is about 80% white, and black men are slightly more represented than black women. Moreover, men performed more sports than women and, in particular, played more team sports and official competitions during adolescence.

Finally, it is useful to note that our samples are comparable across treatments. Kruskal-Wallis and Chi Square tests tell us that the covariate distributions do not statistically differ across treatments (see Table 5 in the Appendix). Within each gender, we also find no statistically significant differences in performance across treatments (see Figure 5 in the Appendix for a visual representation). Table 6 reports the sample size by treatment and gender along with the Stage 2 loss rates.

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reasons for this include the presence of performance feedback after Stage 2, women's superior task performance as well as general differences in the design and participant pool between this study (online with a diverse sample) and previous work (largely in the laboratory with student participants).

Table 1: Descriptive Statistics by Gender

	Female		Male		
Variable	Mean	Sd	Mean	Sd	*p*-value
OUTCOME					
Compete (Stage 3)	0.398	0.49	0.454	0.498	0.009
Won (Stage 2)	0.576	0.494	0.515	0.5	0.005
BELIEFS, ATTITUDES AND PERFORMANCE					
Risk I (Dohmen *et al.*, 2011)	4.759	2.406	5.685	2.444	<0.001
Risk II (Zhang *et al.*, 2019)	1.455	1.118	1.865	1.179	<0.001
Perception men better at the task	4.576	1.726	4.9	1.776	<0.001
Experience of unfairness	1.155	1.132	0.771	1.055	<0.001
Perception of unfairness	3.554	0.817	3.343	0.939	<0.001
Competitive attitude I (Buser *et al.*, 2021b)	4.898	2.651	5.29	2.661	<0.001
Competitive attitude II (Fallucchi *et al.*, 2020)	1.836	1.112	2.369	1.084	<0.001
Competitive attitude III (Duffy & Kornienko, 2010)	2.195	1.121	2.446	1.12	<0.001
Competitive attitude IV	1.545	1.196	1.919	1.245	<0.001
Competitive attitude V	2.087	1.014	2.31	0.945	<0.001
Post feedback rank	53.343	23.489	49.254	25.356	<0.001
Stage 1 score	3.399	1.335	3.157	1.474	<0.001
COVARIATES					
Demographics and Family					
Age	34.568	10.803	35.354	9.195	0.075
Number of male siblings	0.992	1.013	1.047	1.003	0.21
Number of female siblings	0.958	1.016	0.913	0.907	0.288
Number of older siblings	1.965	1.107	1.996	1.023	0.537
Children: yes	0.31	0.463	0.361	0.481	0.014
Children in school: yes	0.225	0.418	0.273	0.446	0.011
Childcare: yes	0.024	0.153	0.044	0.205	0.01
Country of residence: UK	0.184	0.387	0.197	0.398	0.452
Country of residence: US	0.807	0.395	0.803	0.398	0.829
Employment, Education, Ethnicity					
Empl. status: Full time	0.615	0.487	0.825	0.38	<0.001
Empl. status: Not paid work, retired, disabled	0.008	0.091	0.004	0.063	0.218
Empl. status: Part time	0.358	0.48	0.151	0.359	<0.001
Empl. status: Unemployed, job seeking	0.012	0.109	0.008	0.089	0.371
Empl sector: Technology, Engineering & Math	0.042	0.201	0.056	0.23	0.141
Empl sector: Social Sciences	0.032	0.176	0.006	0.077	<0.001
Ethnicity: Asian	0.068	0.252	0.073	0.261	0.639
Ethnicity: Black	0.072	0.258	0.11	0.313	0.002
Ethnicity: White	0.794	0.404	0.774	0.418	0.268
Education: PhD	0.032	0.176	0.047	0.212	0.078
Education: MA., Msc., other	0.185	0.389	0.262	0.44	<0.001
Education: BA., Bsc., other	0.423	0.494	0.393	0.489	0.162
Education: High school	0.19	0.393	0.173	0.378	0.299
Education: Technical college	0.14	0.348	0.1	0.301	0.005
Student: yes	0.185	0.389	0.135	0.342	0.002
Personal Background					
Lived with siblings: yes	0.738	0.44	0.772	0.42	0.071
Sport: yes	0.468	0.499	0.673	0.469	<0.001
Sport type: individual	0.054	0.226	0.053	0.224	0.918
Sport type: team	0.2	0.4	0.291	0.454	<0.001
Sports official competition: yes	0.307	0.461	0.485	0.5	<0.001
Observations	1089		997		2086

Notes. *p*-value from t-tests of gender differences. Variable definitions and descriptions can be found in Table 4 in the Appendix.

4.2 Baseline Results (Neutral Treatment)

We present our main results in Figure 2 and Table 2. Figure 2 plots the fraction of women and men who chose to compete in Stage 3 after winning and losing in Stage 2, respectively. For the baseline (Neutral) treatment in the upper left panel, three results are apparent. First, Stage 2 tournament winners are 38 percentage points more likely to compete than tournament losers ($p < 0.0001$, t-test). Second, the gender gap in tournament entry is small and only marginally significant among tournament winners (8.2pp, $p = 0.099$, t-test), and not statistically significant among losers (2.9pp, $p = 0.508$). Third, men (41 percentage points) and women (36 percentage points) reduce their tournament entry in similar ways after losing in Stage 2 (relative to winning). Hence, while we find strong evidence that participants who lose competitions are less likely to enter subsequent competitions, we do not find evidence that this effect differs by gender.

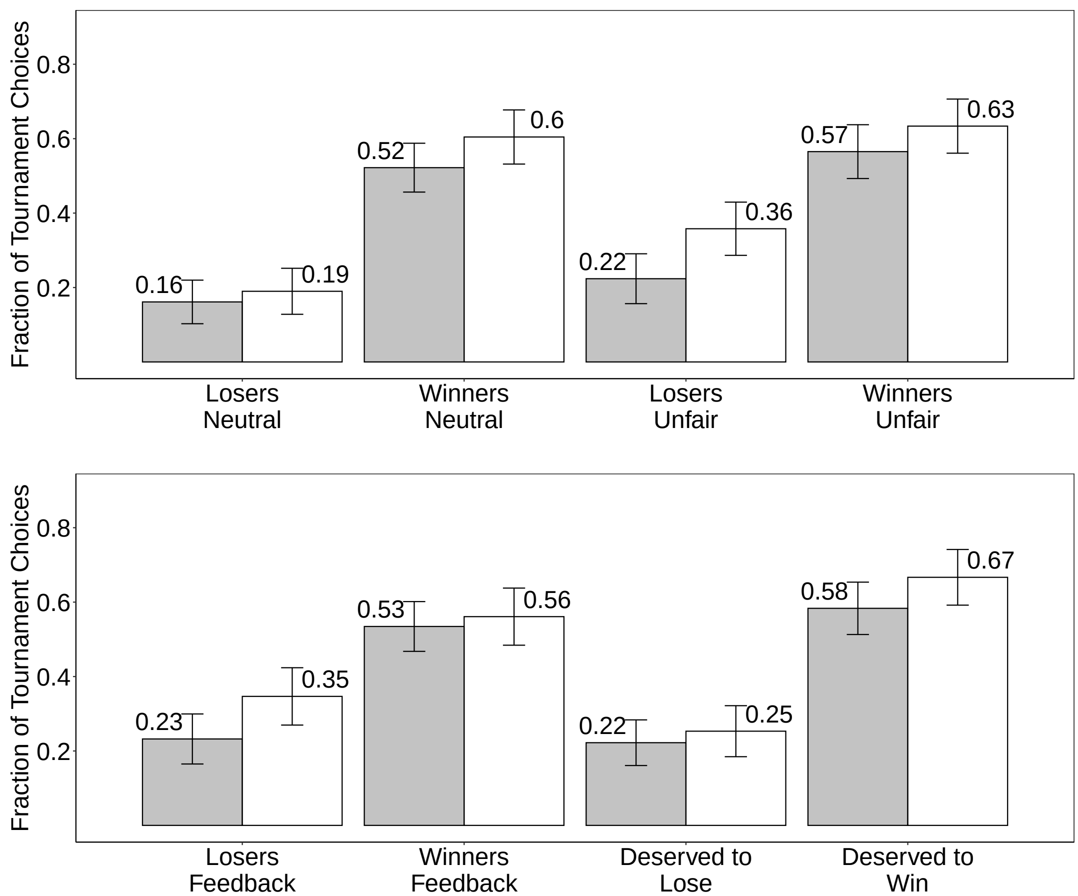
However, these raw differences are potentially confounded by ability differences between winners and losers (and between men and women). Hence, Table 2 examines these associations more formally while also controlling for Stage 1 performance fixed effects, conditional on which winning or losing is a random event.[3] The results are very similar to Figure 2. The term (a) replicates the non-significant gender gap among losers found in Figure 2 (2.9pp in the figure, and 2.1 in the regression) and the term (a+c) replicates the marginally significant gender gap among winners (8.2pp in the figure, and 8.6 in the regression). The difference between winners and losers is also observed both among men (term (b)) and women (b+e). Figure 6 in the Appendix shows that the difference between winners and losers appears for each performance quartile. The interaction term (c) shows that the causal effect of winning (as opposed to losing) a prior competition does not differ significantly by gender.

In line with hypothesis 1, we therefore find strong evidence that winning a prior tournament greatly increases the propensity to enter a subsequent competition. Yet we find no evidence that this effect differs by gender. Hence, both men and women treat the outcome of Stage 2 as a key signal in determining their decision in Stage 3. The lack of an observed gender difference in response to losing a competition stands in contrast to Buser & Yuan (2019), which could be driven by

[3]Our results are robust to controlling for performance in Stage 2 instead.

experimental features (e.g., using a different task, online versus laboratory) and by differences in the sample (students versus our more representative group).[4]

Figure 2: Tournament Entry Decisions



Notes. The figure plots the fraction of participants who decided to enter the tournament by the stage-2 outcome (losers or winners), gender (grey: female, white: male) and treatment (top: Neutral and Unfair, bottom: Feedback). For the Feedback treatment, we also plot the results for participants based on whether they were told they deserved to win the stage-2 tournament. Error bars represent 95% confidence intervals for the fraction of participants choosing the tournament in Stage 3.

[4] The literature's findings on the magnitude of the gender gap in competition *entry* also differ depending on the nature of the sample. For instance, using a representative sample of the Swedish population, Boschini *et al.* (2019) do not replicate the gender gap in tournament entry in a math task found by previous studies.

Table 2: Tournament Entry Regressions

	Coefficient (Std. Errors)		
	Neutral (1)	Unfair (2)	Feedback (3)
	Dep Var: Tournament Entry (Stage 3)		
(a) Female	-0.021	-0.116**	-0.061
	(0.043)	(0.053)	(0.051)
(b) Winner	0.429***	0.204**	0.031
	(0.049)	(0.065)	(0.059)
(c) Winner*Female	-0.065	0.161*	0.135*
	(0.066)	(0.090)	(0.082)
(d) Deserved to Win		0.109	0.398***
		(0.067)	(0.060)
(e) Deserved to Win*Female		-0.144	-0.136*
		(0.090)	(0.082)
Constant	0.181***	0.344***	0.240***
	(0.031)	(0.039)	(0.039)
	Effects for Women		
Winner (b+c)	0.364***	0.365***	0.166***
Deserved to Win (d+e)		-0.035	0.262***
	Treatment Differences (p-values)		
	(1) vs (2)	(1) vs (3)	(2) vs (3)
Winner (b)	0.005***	0.000***	0.048**
Winner*Female (c)	0.040**	0.054*	0.832
Stage 1 Score Fixed Effects	Yes	Yes	Yes
Observations	716	684	686
Adj. R^2	0.156	0.104	0.172

Notes. OLS Estimates, robust standard errors in parentheses. The dependent variable is the Stage 3 choice of compensation scheme (1-tournament, 0-piece rate). "Winner" is a dummy for participants who won the tournament in Stage 2. "Deserved to Win" is a dummy for a participant that would have won a fair tournament in Stage 2. The regressions include Stage 1 score fixed effects. The middle panel present the sum of the respective main effect and gender interaction (the associated p-values are derived using Wald-tests). The final panel presents Wald tests for differences in coefficients between columns.
*** p<0.01, ** p<0.05, * p<0.1

4.3 The Effect of Unfairness (Unfair Treatment)

We now turn to examining the effect of unfairness. Column (2) in Table 2 and the top right panel of Figure 2 present the results for the Unfair Treatment. Despite losing being less predictive of future success in this treatment, Stage 2 winners are still 30.2 pp more likely to enter the tournament in Stage 3 ($p < 0.0001$, t-test). This effect appears in all performance quartiles (Figure 6 in the Appendix) and appears to be more pronounced for women (34.2 percentage points) than for men (27.6 percentage points). Table 2 examines the gender and winner effects while controlling for performance using both Stage 1 score fixed effects and a dummy for whether participants would have won the tournament had the winner been the participant with the highest score ("Deserved to Win"). The interaction term (c) shows that women respond more strongly to the Stage 2 outcome, making female losers significantly less likely to compete than male losers (by 11.6pp, term (a)).

In terms of our predictions, we see that men are indeed much less affected by the Stage 2 outcome (20.4pp) than in the Neutral Treatment (42.9pp, $p = 0.005$, Wald test, term (b)), in line with hypothesis 2. This is sensible, because losing an unfair competition is a less informative signal of relative ability than losing a fair competition. By contrast, and in contrast to hypothesis 2, women interestingly respond just as much to losing in both treatments (36.5pp and 36.4pp, respectively). These two results jointly imply that that the gender gap in response to losing is larger in the Unfair Treatment than in the Neutral Treatment. Formally, the difference between the interaction term (c) in Column (1) and Column (2) is statistically significant ($p = 0.040$, Wald test), in line with our predictions (hypothesis 3).

One other result of note is that tournament entry rates are greater in the Unfair Treatment than in the Neutral Treatment (39.1pp vs. 45.3pp, $p = 0.019$, t-test). This difference is driven by male losers, who compete at much higher rates in the Unfair Treatment (19.0 vs. 35.8pp, $p < 0.001$, t-test), whereas for male winners (60.5pp vs. 63.4pp), for female losers (16.1pp vs. 22.3pp, $p = 0.166$, t-test) and for female winners (52.2 vs. 56.5pp) the differences are small and not statistically significant. This is consistent with motivated reasoning being a factor among men: whereas male winners may have attributed their success to their own ability and therefore competed as much as in the Neutral Treatment, male losers may have attributed their loss to bad luck, and competed at almost twice the rate as in the Neutral Treatment. However, we find less support for motivated beliefs in the belief data where we do not observe that male losers update less in the Unfair treatment (8.5 ranks in the Neutral Treatment, 11.7 in the Unfair Treatment).

Overall, these results demonstrate that introducing unfairness increases the gender gap in the response to losing a competition, in line with hypothesis 3. This result is consistent with at least two potential mechanisms. The first is that women see losing a competition as a more informative signal of their ability than men do. This may be the case if, for example, women are more likely to attribute failure to their own skill (as opposed to game being rigged against them). Alternatively, it may also be that losing a competition directly affects the preference channel, e.g., by increasing risk or disappointment aversion, and this effect is stronger for women. To distinguish between the beliefs and preferences channel we turn to the results of the final treatment.

4.4 Mechanisms (Feedback Treatment)

After Stage 2, participants in the Feedback Treatment were given feedback on the nature of their competition and their ability rank. Assuming that participants understand that this feedback renders the Stage 2 outcome (winning or losing) totally uninformative, this removes the beliefs channel as a potential explanation for differences between winners and losers. Conditional on performance (which is perfectly correlated with performance rank), any residual gender difference in the response to losing or winning in Stage 2 must, therefore, be due to the preferences channel.[5]

Column (3) in Table 2 and the bottom panel of Figure 2 present the results for the Feedback Treatment. When looking at the raw data, both men (21.4pp) and women (30.2pp) in the Feedback Treatment are significantly more likely to compete after winning in Stage 2 ($p < 0.0001$ for both genders). When controlling for performance (and hence performance rank, Table 2), however, these effects are greatly reduced. In fact, conditional on all the feedback they have received, men no longer put any value on winning or losing in Stage 2 (the point estimate is 3.1pp), although female losers are still significantly less likely to compete than female winners (the point estimate (b+c) is 16.6 pp). The interaction term (c) is statistically significant at the 10% level and not significantly different from the interaction term in Column (2). This implies that even when losing a competition is no longer informative about the prospect of winning a future competition, the gender gap in response to losing a tournament remains.

[5] Note that this does not imply that beliefs do not play a role in this treatment. For example, even conditional on the feedback received, it may be that men are still more optimistic about their future win chances than women. The key assumption is that any such (gender) differences are similar for winners and losers, and will therefore not impact our estimate of the difference between these groups.

These differences are also reflected in the role played by the performance feedback participants receive. Male participants now base their decisions on the feedback they received after Stage 2. In particular, the effect of deserving to win the competition (i.e., having a score higher than the random opponent's) is comparable to the effect of actually winning the tournament in the Neutral Treatment. For women, however, the effect of being a "deserving winner" is more muted at 26.2pp. In other words, while both men and women primarily base their entry decisions on the performance feedback they received, women pay relatively less attention to performance feedback and more attention to the actual outcome of Stage 2.[6]

Overall, the result that the gender gap in response to losing an unfair competition remains even in a treatment that removes the beliefs channel suggests that this gap is driven primarily by preferences and not beliefs. As an alternative test of the role of beliefs, we can also examine the results of the belief elicitation tasks. In particular, losing (winning) the Stage 2 tournament should lead participants to become significantly more pessimistic (optimistic) about their win chances in Stage 3. If beliefs do indeed play no role in explaining gender differences in response to losing unfair competitions, then there should not be a gender difference in belief updating either. Our results are consistent with this. In the Neutral Treatment, both men (8.7 ranks) and women (9.5 ranks) update their beliefs significantly in the direction corresponding to the tournament's outcome ($p < 0.0001$, separate t-test for each gender). In the Unfair Treatment, updating reduces to 7.5 ranks for men and 5.9 ranks for women ($p < 0.0001$, t-test for each gender). The gender difference in updating is not statistically significant in either treatment ($p = 0.570$ for the Neutral Treatment, and $p = 0.292$ for the Unfair Treatment, t-tests). If anything, there is a small tendency for women in the Unfair Treatment to update *less* than men (the treatment difference is statistically significant for women, $p = 0.012$, but not for men, $p = 0.404$, t-test). Importantly, this implies that gender differences in belief updating in the Unfair Treatment (women, if anything, update less after Stage 2) cannot explain gender differences in behavior (women respond more to the Stage 2 outcome).

[6]Note that we are unable to do a similar analysis for the rank feedback directly, since rank feedback is perfectly correlated with performance and therefore not an exogenous event.

4.5 Heterogeneous Effects (Machine Learning)

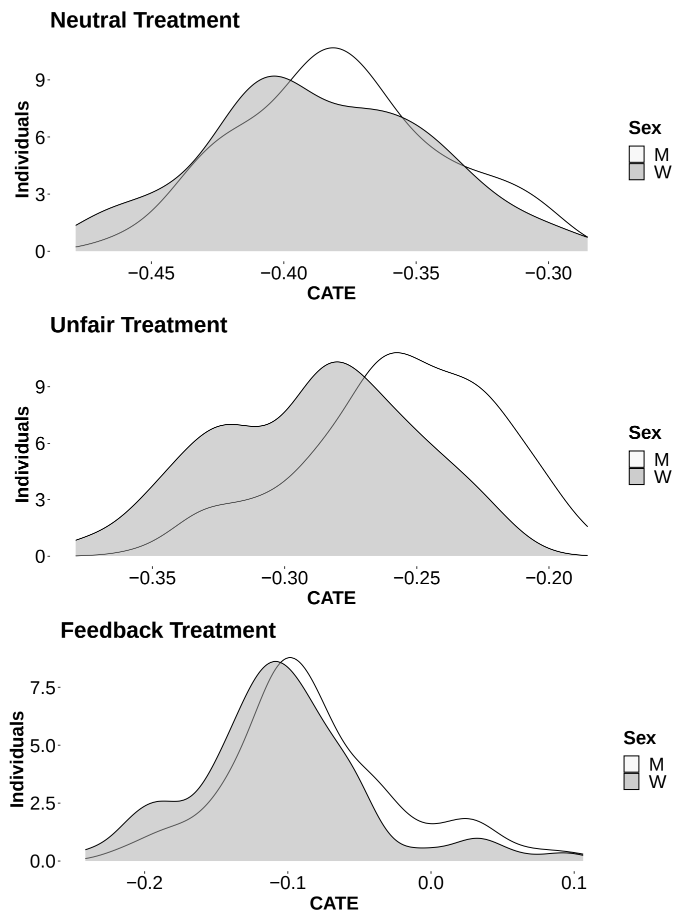
We now turn to our analysis of heterogeneous effects using machine learning techniques. In applying these techniques, our purpose is to understand: (i) whether gender is an important predictor of the response to losing a competition even when we control for a large set of other individual characteristics; and (ii) whether other factors apart from gender might be important determinants of the effect of losing a competition. Beyond providing more insights into the factors driving our observed effects, this analysis may also help generalize results to different populations, potentially improving external validity of our results (Bryan *et al.*, 2021; Imai & Ratkovic, 2013; Manski, 2004).

The specific technique we use is the causal forest estimator (Wager & Athey, 2018; Athey & Wager, 2019; Athey *et al.*, 2019). This estimator allows us to identify the predicted effect of losing a competition conditional on any combination of variables in our data, the so-called *conditional average treatment effect* (CATE, where "treatment" refers to the effect of losing rather than winning in our case). This, in turn, allows us to examine the distribution of individualized CATEs in our sample, and test whether these distributions differ significantly by gender and other observables. Relative to OLS, causal forests have the advantage of limiting discretion in variable selection and model specification. They also make it possible to study high-dimensional non-linearities while avoiding overfitting, through the use of sample splitting into training and estimation samples. We refer to Athey *et al.* (2019) for a full description of the estimator, and to Valente (2023) for more details on the parameter estimation, bootstrap variance estimation, and tuning methods used in this paper.[7] Our analysis includes all variables labeled as covariates in Table 4, plus performance and dummy variables for winning and deserving to win in Stage 2.

Figure 3 plots the predicted CATEs by gender, separately for each treatment. As a first step, it is useful to note that the CATEs of losing a competition are negative and statistically significant for all individuals in the Neutral and Unfair Treatments. In the Feedback Treatment, the CATEs are statistically insignificant for 70% of individuals. In other words, tournament losers are predicted to be less likely to compete in the Neutral and Unfair Treatments but not in the Feedback

[7]For the entire machine learning analysis, we use software R-4.2.1, grf package version 2.2.0 (Tibshirani *et al.*, 2022), and hdm package version 0.3.1 (Martin *et al.*, 2019).

Figure 3: Predicted Effects (CATEs) of Losing a Competition on Tournament Entry.



Notes. The figure plots the distribution of the predicted CATEs of losing a competition, which are obtained using the grf implementation of the causal forest estimator (Athey *et al.*, 2019; Tibshirani *et al.*, 2022). Separate distributions are presented for each treatment and for men (M) and women (W).

Treatment, in line with our previous results.

Also in line with our previous results is that we observe a clear tendency for men to respond less to losing a tournament than women in the Unfair Treatment and to a lesser extent the Feedback Treatment. In particular, both the mean and the median of the distribution of the CATEs of losing differ significantly by gender in the Unfair and Feedback Treatments ($p < 0.01$ using t-tests and Wilcoxon tests for means and medians, respectively). The gender difference is less pronounced in the Neutral Treatment (t-test: $p = 0.08$, Wilcoxon rank sum: $p = 0.11$). In other words, gender remains a statistically significant predictor of the effect of losing in the Unfair and Feedback treatments even when flexibly controlling for a large set of other variables.

As a next step, we examine which factors other than gender may be important determinants of the effect of losing in each treatment. We do so by regressing the predicted CATEs on all controls, and perform model selection using the lasso estimator (after standardizing the data). Lasso is a regularization technique used in linear regression models to reduce the complexity and improve the interpretability of the model. In standard linear regressions, the objective is to minimize the sum of squared residuals between the predicted values and the actual values. However, in lasso regressions, an additional penalty term is introduced that encourages the model to shrink the coefficients of less important predictors towards zero. By eliminating the coefficients of irrelevant predictors, lasso helps to address issues of multicollinearity and overfitting. By selecting the predictors with the most explanatory power, lasso provides a more parsimonious and interpretable model without sacrificing predictive accuracy.

Table 3 presents the predictors selected by lasso, ordered based on their individual contributions to explaining the heterogeneity of treatment effects (CATEs). The measure used to assess their contributions is the proportion of total variance in the effect of losing explained by each predictor. As a starting point, it is useful to see that gender once again emerges as the main predictor in explaining the effect of losing in the Unfair treatment, and is less important but still selected in the Feedback treatment.

Table 3 also shows that several other factors are important predictors of the effect of losing as well. Specifically, we find that age, having practiced sports in adolescence, and the number of male siblings are among the best and most recurrent predictors of the effect of losing in all treatments. Interestingly, age explains most of the variation in the effect of losing in the Neutral treatment, with older people being less responsive to losing overall. In the other two treatments, the heterogeneity in the effect of losing appears to be driven by a larger set of variables, with the largest role being played by gender and the number of male siblings respectively.

Table 3: Main Predictors of the Effect of Losing after Model Selection via Lasso

	Dep Var: The Effect of Losing (CATEs)	
Neutral	Predictors of Effect Heterogeneity	Var.Expl.%
	Age	0.65
	Stage 1 Score	0.05
	Sport: yes	0.04
	Number of children	0.02
	Number of male siblings	0.02
	Education: Technical college	0.02
Unfair	Predictors of Effect Heterogeneity	Var.Expl.%
	Gender	0.17
	Sport: yes	0.09
	Stage 1 Score	0.07
	Employment status: Full time	0.04
	Employment sector: Retail	0.04
	Education: Technical college	0.03
	Children in school: yes	0.02
	Age	0.02
Feedback	Predictors of Effect Heterogeneity	Var.Expl.%
	Number of male siblings	0.24
	Children: yes	0.17
	Sport type: team	0.07
	Age	0.06
	Gender	0.03
	Number of older siblings	0.03
	Number of children	0.02

Notes. Main predictors of the effect of losing, estimated as conditional average treatment effects (CATEs) using causal forests. The second column shows the main predictors selected by lasso in each treatment. The third column reports the proportion of total treatment effect variance explained by each predictor. This measure is computed by dividing the sum of squares of the effect by the total sum of squares. Predictors with 1% or less contribution to the total variance are not reported. The three panels present the results of the three treatments respectively.

It is possible to get a better sense of the magnitude of these effects by including the variables selected by lasso as additional controls in Table 2. To avoid potential multicollinearity issues in OLS and to ease interpretability, we only include the main covariate selected in each treatment (other than gender). The results of our analysis are reported in Table 7 in the Appendix. First, the interaction terms reveal that older participants (treatment Neutral), participants who practiced sports (treatment Unfair) and participants with more male siblings (treatment Feedback) respond less strongly to losing a competition. Second, the main effect of the latter two variables is also significant, suggesting that practicing sports and having more male siblings positively predicts tournament entry. Third, the gender gap (c) in the effect of losing is is reduced when we control for, in particular, the sports variable in coulumn (2). In our sample, women practiced significantly less sports than men in adolescence (45% did so vs. 69%, $p < 0.0001$, Chi-square test). Controlling for sports absorbs one third of the effect of gender in unfair competitions (from 16 to 11 pp) and renders the coefficient statistically insignificant. However, this finding must be interpreted with care. On the one hand, it suggests that sports in adolescence might help increasing resilience to unfair competition outcomes. On the other hand, it may be the result of self-selection by individuals with greater confidence or preferences for risk and competition.

5 Conclusion

We study gender differences in persistence after losing a competition using an online experiment. We find strong evidence that both male and female participants who lost rather than won a tournament are less likely to enter a subsequent competition. Importantly, however, this effect differs by gender only in a treatment where an inferior performer may have won the tournament. In other words, women are less persistent than men after experiencing failure when they know that failure may have been the result of unfairness. We are able to corroborate these results using causal forests. We also present evidence that this difference is not due to gender differences in belief updating, and may therefore instead be attributed to a discouragement effect on women's preferences for entering future competitions.

An implication of our results is that women may be particularly negatively affected by experiences of failure in the presence of a perception of unfairness. This is unfortunate, because such perceptions appear to be highly prevalent in society, where we can often find ways to attribute our failures to factors outside of our control (e.g., a reviewer's mood, real or perceived nepotism, favoritism, or other forms of discrimination, see, e.g., Gagliarducci & Manacorda 2020). At the same time, it is in some sense reassuring that, unlike Buser & Yuan (2019), we do not find a gender gap in persistence after losing a fair tournament. This implies that organizations may be able to reduce gender differences by introducing fair and transparent assessment procedures that reduce the perceptions of unfairness.

One advantage of our large sample size and extensive number of control variables is that we are able to go beyond average effect estimates by drawing on machine learning methods. These techniques allow us to elaborate on heterogeneity in the effect of losing in a disciplined way. We rely on a data-driven procedure with promising features regarding estimation of conditional average treatment effects that helps mitigate potential issues stemming from overfitting, p-hacking, and—importantly—ad-hoc assumptions on which demographics to include and how to precisely model them. Corresponding results suggest that age, experience with sports, and the number of male siblings may explain some of the heterogeneities we observe.

A feature of our design is that unfairness affected all participants in an equal way. In some applications, however, unfairness may be (perceived to be) targeted towards specific parts of the population. Hence, an interesting question for future research is whether our results generalize to such settings. For example, do men and women still respond differently to losing when quotas—which may also be perceived as unfair—are in place? Similarly, it may be worthwhile studying how the experience of unfairness affects tournament entry when the subsequent tournament may also be seen as unfair, as may be the case with affirmative action policies.

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Online Appendix

A Conceptual Framework for Belief Updating after Losing a Competition

In the Hypotheses Section, we argued that losing the tournament in Stage 2 presents a negative signal of ability that should make participants more pessimistic about their win chances in Stage 3. We also argued that this signal is weaker in the Unfair Treatment than in the Neutral Treatment. In this section, we present a simple conceptual Bayesian updating framework that provides the basis for these claims. For this purpose, we will first present our basic framework and illustrate our main intuition using a simple example. We will then also present a more general case.

A.1 Main Framework

We start by examining how a participant should update their subjective probability of winning the Stage 3 tournament based on the outcome in Stage 2. For this purpose, we will derive expressions for the conditional subjective probability of winning in Stage 3 based on winning or losing in Stage 2, i.e., $p_i^s(W_3|W_2)$ and $p_i^s(W_3|L_2)$ respectively. We will also use the unconditional subjective probability of winning a tournament ($p_i^s(W)$) as well as someone's true probability of winning a tournament ($p_i(W)$).

As a first step, it is useful to note that, within the context of our experiment, there is a one-to-one correspondence between a participant's win probability ($p_i(W)$) and their rank r relative to the sample of 100 possible opponents. Noting that the first-ranked participant has a 100% chance of winning, the second-ranked a 99% chance of winning, et cetera, we can write the probability for participant i of winning a tournament conditional (W) on achieving a certain rank r as $p^r(W|r_i = r) = \frac{101-r}{100}$. This allows us to think of participant i's rank $r_i \in R = \{1, ..., 101\}$ as her type, where we assume that her true type is constant over time (and hence identical in Stage 2 and Stage 3).

Our goal in this section is to compute the optimal posterior win probability for Stage 3 after winning the tournament in Stage 2 $p_i^s(W_3|W_2)$. We can do this in three steps. First, we compute the posterior probability $p_i^s(r_i = r|W_2)$ that a tournament winner in Stage 2 believes they are of a certain rank r given their prior $p_i^s = p_i^s(p_i^s(r_i = 1), \ldots, p_i^s(r_i = 101))$. Note that the prior is a vector, where each element describes how likely participant i thinks she is of each potential type (i.e., rank). After winning the tournament in Stage 2, a Bayesian participant would then update her belief about the likelihood about being a given rank r as follows:

$$p_i^s(r_i = r|W_2) = \frac{p_i^s(r_i = r) * p^r(W_2|r_i = r)}{p_i^s(W_2)} = \frac{p_i^s(r_i = r) * \frac{101-r}{100}}{\sum_{k \in R} \frac{101-k}{100} * p_i^s(r_i = k)} \quad (2)$$

Here, the first step follows from the definition of a conditional probability, where the second uses the one-to-one correspondence between ranks and win probabilities. Noting that the expected posterior rank $E(r_i|W_2) = \sum_{k \in R} p_i^s(r_i = k|W_2) * k$, we can then express the posterior win probability as:

$$p_i^s(W_3|W_2) = \frac{101 - E(r_i|W_2)}{100} \quad (3)$$

A.2 A Simple Example

Let us illustrate these concepts using a simple example. In particular, let us assume that participant i believes to be either rank 11 (i.e., a 90% win chance) or rank 71 (i.e., a 30% win chance) with equal probability. In this case, her prior p_i^s implies that $p_i^s(r_i = 11) = p_i^s(r_i = 71) = 0.5$, and all other ranks have a prior probability of zero. The posterior probability of being rank 11 will then be equal to:

$$p_i^s(r_i = 11|W_2) = \frac{p_i^s(r_i = 11) * p^r(W_2|r_i = 11)}{p_i^s(W_2)} = \frac{0.5 * 0.9}{0.5 * 0.9 + 0.5 * 0.3} = 0.75 \quad (4)$$

And similarly, $p_i^s(r_i = 71|W_2) = 0.25$. Intuitively, the high type (rank 11, 90%) is three times more likely to win the Stage 2 tournament than the low type (rank 71, 30%). With an even (50/50) prior, this implies that participant i thinks she is three times more likely to be a high type than being a low type after observing a victory in the Stage 2 tournament. This, in turn, means that observing a tournament win in Stage 2 increases her subjective win probability from $p_i^s(W_3) = 0.5 * 0.9 + 0.5 * 0.3 = 0.6$ to $p_i^s(W_3|W_2) = 0.75 * 0.9 + 0.25 * 0.3 = 0.75$.

In the Unfair Treatment, there is a 25% chance that the inferior performer wins the tournament in Stage 2. It is useful to note that this is equivalent to a setting where the winner is based on merit half the time and determined randomly in the other 50% of cases. As a result, it is easy to see that the tournament outcome is a 50% weaker signal compared to the Neutral treatment. The posterior of being rank r in the Unfair treatment will therefore be as follows:

$$p_i^s(r_i = r|W_2) = \frac{(0.75 * \frac{101-r}{100} + 0.25 * \frac{r-1}{100}) * p_i^s(r_i = r)}{\sum_{k \in R}(0.75 * \frac{101-k}{100} + 0.25 * \frac{k-1}{100}) * p_i^s(r_i = k)} \tag{5}$$

Turning back to the simple example, this would imply that the posterior probability of being rank 11 would be equal to:

$$p_i^s(r_i = 11|W_2) = \frac{p_i^s(r_i = 11) * p_i^s(W_2|r_i = 11))}{p_i^s(W_2)} = \frac{0.5 * 0.7}{0.5 * 0.7 + 0.5 * 0.4} \approx 0.64 \tag{6}$$

This uses the fact that the win probability for a ranked-11 individual equals $(0.9 * 0.75 + 0.1 * 0.25) = 0.70$. Equation (6) shows that, while winning the tournament still provides some information value in the Unfair Treatment, the overall information value is markedly less than in the Neutral Treatment. The posterior probability (0.64) is only 14 percentage points higher than the prior, whereas in the Neutral treatment the difference was 25 percentage points. Her subjective win probability in this treatment changes from $p_i^s(W_3) = 0.5 * 0.9 + 0.5 * 0.3 = 0.6$ to $p_i^s(W_3|W_2) = 0.64 * 0.9 + 0.36 * 0.3 \approx 0.68$ after observing the win in Stage 2, and, therefore, also changes less (8 percentage points) than in the Neutral Treatment (15 percentage points).

For our final treatment (Feedback Treatment), participants know whether they previously played a fair or unfair tournament. If the tournament was fair, the posterior is identical to the posterior for the Neutral Treatment. If the tournament was unfair, a win should be interpreted the same as a loss in the Neutral Treatment. Note, however, that we also informed all participants in this treatment about their exact rank after completing Stage 2. If participants treat their type (i.e., rank) as constant across the two stages, this would give them perfect information about their win chance in the unfair tournament, removing the need for Bayesian updating.

A.3 A More General Case

So far, we have seen that winning or losing a tournament has more information value in the Neutral than in the Unfair Treatment in a simple example. Figure 4 shows that this also holds more generally. In particular, the Figure plots the posterior probability of winning a tournament after losing a prior competition as the function of the prior subjective probability of winning. As in the simple example, winning a tournament has more information value (graph further away from the 45 degree line) in the Neutral Treatment than in the Unfair Treatment. We will now present further details for the derivation of Figure 4.

Figure 4: Theoretical predictions for posteriors in the Neutral (solid black line) and Unfair (solid grey line) treatments.

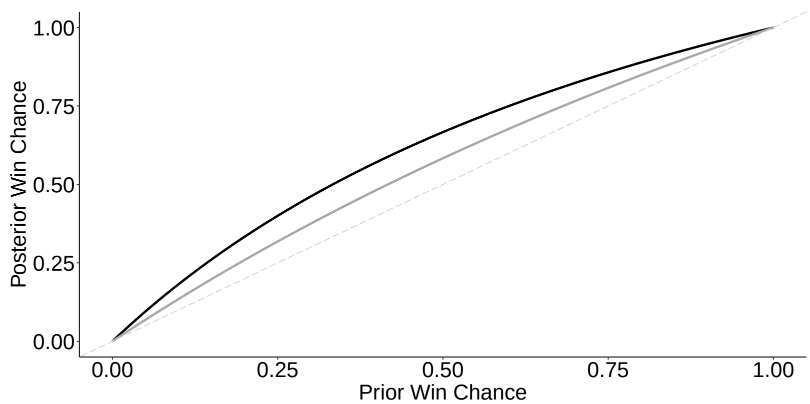

Figure 4 plots the posterior win chance as a function of the prior and the treatment. Deriving the optimal Bayesian posteriors conditional on a given prior is complicated by the fact that we only elicited the expected rank $E(r_i|W_2)$ instead of the full prior $p_i^s = p_i^s(p_i^s(r_i = 1), \ldots, p_i^s(r_i = 101))$. As a result, we are unable to use Equation (2) directly. However, we can approximate the optimal posterior $p_i^s(W_3|W_2)$ using the one-to-one correspondence between the expected rank and the subjective win probability. By Bayes' Theorem, we obtain

$$p_i^s(W_3|W_2) = \frac{p_i^s(W_2 \& W_3)}{p_i^s(W_2)} = \frac{p_i^s(W_2|W_3) * p_i^s(W_3)}{p_i^s(W_2|W_3) * p_i^s(W_3) + p_i^s(W_2|L_3) * (1 - p_i^s(W_3))} \tag{7}$$

To obtain an expression for $p_i^s(W_3|W_2)$, we make two further assumptions. First, we assume that $p_i^s(W_3) = p_i^s(W_2)$. That is, we assume that participants have the same (unconditional) subjective probability of winning the Stage 2 and Stage 3 tournaments. Effectively, this is a fairly innocuous assumption that postulates that participants have no particular ex ante reason to believe that they will do better at either of the two tournaments (prior to receiving feedback).

Second, we assume that $p_i^s(W_2|W_3)$ and $p_i^s(W_2|L_3)$ are equal to their population averages $p^p(W_2|W_3)$ and $p^p(W_2|L_3)$, for any possible prior. This will clearly not be the case for every individual participant, since participants with optimistic priors will almost certainly have higher values for $p_i^s(W_2|W_3)$ and $p_i^s(W_2|L_3)$ than the population average. However, the assumption is likely to hold at least approximately across all participants. Importantly, making this assumption allows us to generate quantitative predictions for how the posterior probability $p_i^s(W_3|W_2)$ will differ by treatment even without data on participants' prior rank distributions. In particular, in the Neutral Treatment we obtain:

$$p^p(W_2|W_3) = \frac{p^p(W_3\&W_2)}{p^p(W_2)} = \frac{\int_{x_i} F(x_i)^2 f(x_i)}{\int_{x_i} F(x_i) f(x_i)} = \frac{\int_0^1 p^2 dp}{\int_0^1 p dp} = \frac{1/3}{1/2} = \frac{2}{3} \tag{8}$$

Here, the first step follows from the definition of a conditional probability. The second step assumes that performance x_i is distributed according to some continuous cumulative density function $F(x_i)$ with probability density function $f(x_i)$. This assumption implies that, for a given performance x_i, the probability of winning a tournament equals the probability that participant i's performance is superior to the performance of a randomly chosen opponent (x_j), i.e., that $p(W|x_i) = p(x_i > x_j) = F(x_i)$ and hence $p(W_3\&W_2|x_i) = F(x_i)^2$. The proportion of winners in the population can then be found by summing over all performance levels. The third step uses the fact that, by the universality of the uniform, the win probability $F(x_i) = p$ is itself standard uniformly distributed.

Following a similar logic, we can also obtain that $p^p(W_2|L_3) = \frac{1}{3}$. These results tell us that the winners of a given tournament ($p^p(W_2|W_3) = \frac{2}{3}$) are twice as likely to win a second tournament as tournament losers ($p^p(W_2|L_3) = \frac{1}{3}$) in the population. While the actual subjective $p_i^s(W_2|W_3)$ and $p_i^s(W_2|L_3)$ may differ for individual participants, the population proportions provide a useful approximation across all participants in the sample. We can then plug these expressions into Equation (7) to obtain:

$$p_i^s(W_3|W_2) = \frac{\frac{2}{3}p_i^s(W_3)}{\frac{2}{3}p_i^s(W_3) + \frac{1}{3}(1 - p_i^s(W_3))} = \frac{\frac{2}{3}p_i^s(W_3)}{\frac{1}{3}(1 + p_i^s(W_3))} = \frac{2p_i^s(W_3)}{1 + p_i^s(W_3)} \tag{9}$$

For the Unfair Treatment, a similar logic applies, except that there is a 50% chance that the winner in tournament 2 is determined at random. This implies that $p_i^s(W_2|W_3) = 0.5(0.5 + 2/3) = \frac{7}{12}$ and hence:

$$p_i^s(W_3|W_2) = \frac{\frac{7}{12}p_i^s(W_3)}{\frac{7}{12}p_i^s(W_3) + \frac{5}{12}(1 - p_i^s(W_3))} = \frac{7p_i^s(W_3)}{5 + 2p_i^s(W_3)} \tag{10}$$

Figure 4 plots the results for the two treatments.

B Variable Descriptions

Table 4: List of Variables and Description

Variable	Description
COVARIATES	
Age	What is your date of birth?
Number of male siblings	How many male siblings do you have (including half siblings)? (0 - 4 or more)
Number of female siblings	How many female siblings do you have (including half siblings)? (0 - 4 or more)
Number of older siblings	How many of your siblings are older than you? (0 - 4 or more)
Lived with siblings	Have you lived in the same household with your sibling(s) during your childhood/adolescence (up to 18 years old)? (yes, only for some time, no)
Number of children	How many children under 16 years old live in your current household? (0 - 4 or more)
Children: yes	Dummy = 1 if Number of children $>$ 0, 0 otherwise
Children in school	Are your children under 16 years old currently going to school? (yes, no, no but they follow homeschooling)
Childcare	Do you benefit from childcare (including babysitters, relatives etc.)? (yes, no, my children spend most of the time with me/my partner, No, my children are independent and do not need childcare)
Ethnicity	What ethnic group do you belong to? (White, Black, Asian, Mixed)
Sport: yes	Did you do sports (outside of the required courses in school) at least once a week from 6 to 18 years old?
Sport type	Which kind of sport did you do from 6 to 18 years old? (single, team, both)
Sports official competition	Did you participate to official competitions regularly from 6 to 18 years old? (yes, no)
Country of residence	What is your country of residence? (USA, UK)
Education	Which of these is the highest level of education you have completed? (PhD; MA., Msc., other; BA, Bsc, other; high school; technical college)
Student	Are you a student? (yes, no)
Employment status	What is your employment status ? (start a new job within a month; full time; no paid, retired disable; part time; unemployed, job seeking, other)
Employment sector	Which of the following best describes the sector you primarily work in? (Agriculture, Food & Natural Resources; Architecture & Constructions; Arts; Business Management & Administration; Education & Training; Finance; Government & Public Administration; Hospitality & Tourism; Information Technology; Legal; Manufacturing; Marketing & Sales; Medicine; Military; Policing; Retail; Technology, Engineering & Math; Social Sciences; Transportation, Distribution & Logistic; Other)
BELIEFS, ATTITUDES AND PERFORMANCE	
Risk I	How do you see yourself: Are you generally a person who is willing to take risks, or do you try to avoid taking risks? (0 not at all willing to take risks - 10 very willing to take risks)
Risk II	Please indicate the degree to which you agree or disagree with this statement: ”My friends would say that I’m a risk taker.” (0 strongly disagree - 4 strongly agree)
Perception men better at the task	Do you think men or women generally do better in the ”counting zeros” task? (0 women do a lot better - 10 men do a lot better)
Experience of unfairness	Have you ever experienced discrimination against you at work (or in the job search) because of, for example, your country of origin, language, cultural group, ethnicity, gender, or family situation? (0 not at all - 4 very often)
Perception of unfairness	Imagine that someone else experiences discrimination at work (or in the job search) because of, for example, her/his country of origin, language, cultural group, ethnicity, gender, or family situation. How disappointed would you be? (0 not at all - 4 extremely disappointed)
Competitive attitude I	How competitive do you consider yourself to be? (0 very much - 10 not at all)
Competitive attitude II	Competitiveness is defined as having a strong desire to win or be the best at something. Based on this definition, please answer the questions below. To which degree do you think the following statement describes you? (0 Not at all like me - 4 Exactly like me) “Competition brings the best out of me.”
Competitive attitude III	Competitiveness is defined as having a strong desire to win or be the best at something. Based on this definition, please answer the questions below. Do you feel that winning or losing matters to you? (0 not at all - 4 very much)

Continued on next page

Competitive attitude IV	Competitiveness is defined as having a strong desire to win or be the best at something. Based on this definition, please answer the questions below. Would you like to be more competitive? (0 not at all - 4 very much)
Competitive attitude V	Competitiveness is defined as having a strong desire to win or be the best at something. Based on this definition, please answer the questions below. On average, how competitive are your closest friends? (0 not at all - 4 very much)
Pre feedback rank	Please guess your rank in Stage 2 compared to 100 previous participants. Please choose a value between 1 (you believe your were the best) and 101 (you believe you were the worst)
Post feedback rank	Before moving on to Stage 3, you have the opportunity to update your estimated rank based on the outcome of the ”Tournament Task” you just did. Please enter your new estimate here by choosing a value between: 1 (you believe you were the best) and 101 (you believe you were the worst):
Stage 1 Score	Number of table whose number of 0s has been reported correctly in Stage 1.
Stage 2 Score	Number of table whose number of 0s has been reported correctly in Stage 2.
Stage 3 Score	Number of table whose number of 0s has been reported correctly in Stage 3.
OUTCOME	
Compete	Decision to compete again in Stage 3 (0 - 1)
Won	Whether participants won in Stage 2 (0 - 1).

C Additional Summary Statistics

Table 5: Summary Statistics for the Full Sample by Treatment

	Neutral	mean	sd	min	max	**Unfair**	mean	sd	min	max	**Feedback**	mean	sd	min	max	$\Delta pvalue$
COVARIATES																
Age	714	34.8	9.6	18	62	683	34.8	10.3	18	73	685	35.3	10.3	18	67	0.7247
Number of male siblings	716	0.95	0.96	0	4	684	1.08	1.05	0	4	686	1.03	1.01	0	4	0.102
Number of female siblings	712	0.93	0.94	0	4	682	0.99	1.03	0	4	686	0.89	0.93	0	4	0.446
Number of older siblings	647	1.98	1.03	1	5	616	1.97	1.09	1	5	616	1.99	1.08	1	5	0.809
Number of children	716	0.59	0.91	0	4	684	0.55	0.89	0	4	686	0.54	0.88	0	4	0.5908
Lived with siblings: yes	716	0.77	0.42	0	1	684	0.74	0.44	0	1	686	0.75	0.43	0	1	0.303
Lived with siblings: some time	716	0.098	0.30	0	1	684	0.11	0.32	0	1	686	0.10	0.30	0	1	0.570
Lived with siblings: no	716	.034	0.18	0	1	684	0.05	0.22	0	1	686	.044	0.20	0	1	0.312
Children in school: yes	716	0.25	0.43	0	1	684	0.25	0.43	0	1	686	0.25	0.43	0	1	0.963
Children in school: no	716	0.077	0.26	0	1	684	0.06	0.23	0	1	686	0.05	0.21	0	1	0.050
Children in school: no, homeschooling	716	0.03	0.16	0	1	684	0.03	0.16	0	1	686	0.03	0.16	0	1	0.941
Childcare: yes	716	0.04	0.20	0	1	684	0.03	0.16	0	1	686	0.03	0.18	0	1	0.403
Childcare: no, children stay with parents	716	0.05	0.22	0	1	684	0.05	0.21	0	1	686	0.04	0.20	0	1	0.767
Childcare: no independent children	716	0.01	0.11	0	1	684	0.01	0.10	0	1	686	0.00	0.04	0	1	0.052
Ethnicity: Asian	716	0.06	0.24	0	1	684	0.07	0.25	0	1	686	0.08	0.28	0	1	0.236
Ethnicity: Black	716	0.09	0.29	0	1	684	0.08	0.28	0	1	686	0.09	0.29	0	1	0.751
Ethnicity: White	716	0.78	0.41	0	1	684	0.78	0.41	0	1	686	0.79	0.41	0	1	0.996
Ethnicity: Mixed	716	0.06	0.24	0	1	684	0.06	0.25	0	1	686	0.04	0.19	0	1	0.047
Number of years of sport during adolescence	716	4.55	4.80	0	12	684	4.64	4.72	0	12	686	4.29	4.55	0	12	0.539
Sport type: single	716	0.04	0.21	0	1	684	0.05	0.23	0	1	686	0.06	0.24	0	1	0.327
Sport type: team	716	0.24	0.43	0	1	684	0.25	0.44	0	1	686	0.23	0.42	0	1	0.690
Sport type: both	716	0.27	0.44	0	1	684	0.26	0.44	0	1	686	0.27	0.44	0	1	0.9531
Sports official competition: yes	716	0.38	0.49	0	1	684	0.40	0.49	0	1	686	0.39	0.49	0	1	0.744
Country of residence: UK	716	0.18	0.38	0	1	684	0.21	0.41	0	1	686	0.18	0.38	0	1	0.197
Country of residence: US	716	0.82	0.39	0	1	684	0.78	0.41	0	1	686	0.81	0.39	0	1	0.214
Education: PhD	716	0.041	0.20	0	1	684	0.03	0.18	0	1	686	0.04	0.20	0	1	0.617
Education: MA., Msc., other	716	0.22	0.42	0	1	684	0.22	0.42	0	1	686	0.22	0.42	0	1	0.995
Education: BA., Bsc., other	716	0.39	0.49	0	1	684	0.42	0.49	0	1	686	0.41	0.49	0	1	0.569
Education: High school	716	0.18	0.39	0	1	684	0.19	0.39	0	1	686	0.17	0.38	0	1	0.515
Education: Technical college	716	0.13	0.34	0	1	684	0.098	0.30	0	1	686	0.14	0.34	0	1	0.070
Student: yes	716	0.16	0.36	0	1	684	0.18	0.38	0	1	686	0.15	0.36	0	1	0.461
Empl. status: Start new job within a month	716	0.00	0.00	0	1	684	0.00	0.05	0	1	686	0.00	0.04	0	1	0.353
Empl. status: Full time	716	0.73	0.45	0	1	684	0.71	0.46	0	1	686	0.71	0.45	0	1	0.675
Empl. status: No paid work, retired, disable	716	0.00	0.06	0	1	684	0.01	0.09	0	1	686	0.01	0.09	0	1	0.693
Empl. status: Part time	716	0.25	0.43	0	1	684	0.26	0.44	0	1	686	0.27	0.44	0	1	0.702
Empl. status: Unemployed, job seeking	716	0.01	0.11	0	1	684	0.01	0.11	0	1	686	0.01	0.08	0	1	0.393
Empl. status: Other	716	0.01	0.07	0	1	684	0.01	0.10	0	1	686	0.00	0.05	0	1	0.219
Empl. sector: Agriculture, Food & Natural Resources	716	0.01	0.12	0	1	684	0.03	0.16	0	1	686	0.01	0.11	0	1	0.081

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Empl. sector: Architecture & Constructions	716	0.03	0.17	0	1	684	0.02	0.16	0	1	686	0.02	0.14	0	1	0.468
Empl. sector: Arts	716	0.05	0.22	0	1	684	0.05	0.21	0	1	686	0.03	0.18	0	1	0.253
Empl. sector Business Management and Admin.	716	0.04	0.19	0	1	684	0.03	0.16	0	1	686	0.02	0.16	0	1	0.417
Empl. sector: Education & Training	716	0.14	0.35	0	1	684	0.16	0.37	0	1	686	0.16	0.37	0	1	0.596
Empl. sector: Finance	716	0.05	0.22	0	1	684	0.06	0.23	0	1	686	0.05	0.22	0	1	0.965
Empl. sector: Government & Public Admin.	716	0.06	0.24	0	1	684	0.04	0.20	0	1	686	0.06	0.24	0	1	0.274
Empl. sector: Hospitality & Tourism	716	0.03	0.18	0	1	684	0.02	0.15	0	1	686	0.03	0.16	0	1	0.503
Empl. sector: Information Technology	716	0.10	0.30	0	1	684	0.09	0.29	0	1	686	0.09	0.28	0	1	0.842
Empl. sector: Legal	716	0.02	0.13	0	1	684	0.02	0.14	0	1	686	0.02	0.14	0	1	0.844
Empl. sector: Manufacturing	716	0.04	0.21	0	1	684	0.04	0.18	0	1	686	0.04	0.20	0	1	0.613
Empl. sector: Marketing & Sales	716	0.03	0.18	0	1	684	0.03	0.16	0	1	686	0.03	0.17	0	1	0.712
Empl. sector: Medicine	716	0.08	0.28	0	1	684	0.09	0.29	0	1	686	0.09	0.28	0	1	0.807
Empl. sector: Military	716	0.00	0.06	0	1	684	0.00	0.07	0	1	686	0.00	0.04	0	1	0.576
Empl. sector: Policing	716	0.01	0.07	0	1	684	0.00	0.00	0	0	686	0.00	0.05	0	1	0.149
Empl. sector: Retail	716	0.09	0.29	0	1	684	0.08	0.28	0	1	686	0.09	0.28	0	1	0.906
Empl. sector: Technology, Engineering & Math	716	0.05	0.22	0	1	684	0.04	0.20	0	1	686	0.06	0.23	0	1	0.393
Empl. sector: Social Sciences	716	0.02	0.13	0	1	684	0.02	0.13	0	1	686	0.02	0.16	0	1	0.495
Empl. sector: Transportation, Distribution & Logistic	716	0.03	0.16	0	1	684	0.03	0.18	0	1	686	0.02	0.16	0	1	0.685
Empl. sector: Other	716	0.11	0.32	0	1	684	0.14	0.35	0	1	686	0.14	0.34	0	1	0.308
BELIEFS, ATTITUDES AND PERFORMANCE																
Risk I	716	5.16	2.56	0	10	684	5.23	2.49	0	10	686	5.22	2.36	0	10	0.833
Risk II	716	1.64	1.21	0	4	684	1.65	1.16	0	4	686	1.66	1.12	0	4	0.844
Perception men better at the task	716	4.73	1.67	0	10	684	4.81	1.77	0	10	686	4.65	1.82	0	10	0.293
Experience of unfairness	716	0.94	1.12	0	4	684	0.95	1.09	0	4	686	1.03	1.13	0	4	0.216
Perception of unfairness	716	3.40	0.92	0	4	684	3.49	0.85	0	4	686	3.48	0.88	0	4	0.131
Competitive attitudes I	716	5.18	2.67	0	10	684	5.01	2.69	0	10	686	5.06	2.62	0	10	0.509
Competitive attitudes II	716	2.03	1.13	0	4	684	2.13	1.15	0	4	686	2.11	1.12	0	4	0.259
Competitive attitudes III	716	2.26	1.17	0	4	684	2.38	1.11	0	4	686	2.30	1.10	0	4	0.186
Competitive attitudes IV	716	1.67	1.23	0	4	684	1.79	1.24	0	4	686	1.72	1.23	0	4	0.209
Competitive attitudes V	716	2.21	1.00	0	4	684	2.24	0.95	0	4	686	2.13	1.01	0	4	0.156
Pre feedback rank	716	51.6	21.5	1	101	684	49.0	22.6	1	101	686	51.2	24.0	1	101	0.0730
Post feedback rank	716	51.4	25.3	1	101	684	51.7	24.1	1	101	686	/	/	/	/	0.8420
Stage 1 Score	716	3.33	1.42	0	9	684	3.28	1.39	0	9	686	3.23	1.41	0	8	0.279
Stage 2 Score	716	3.50	1.37	0	9	684	3.47	1.43	0	10	686	3.47	1.42	0	9	0.763
Stage 3 Score	716	3.84	1.46	0	8	684	3.78	1.55	0	10	686	3.81	1.48	0	7	0.731

Notes. p-value from statistical tests of the distributional differences in covariates. Chi Square test for dummy variables and Kruskal-Wallis test for continuous variables.

Figure 5: Distribution of Stage 1 Scores across Treatments (top: male, bottom: female)

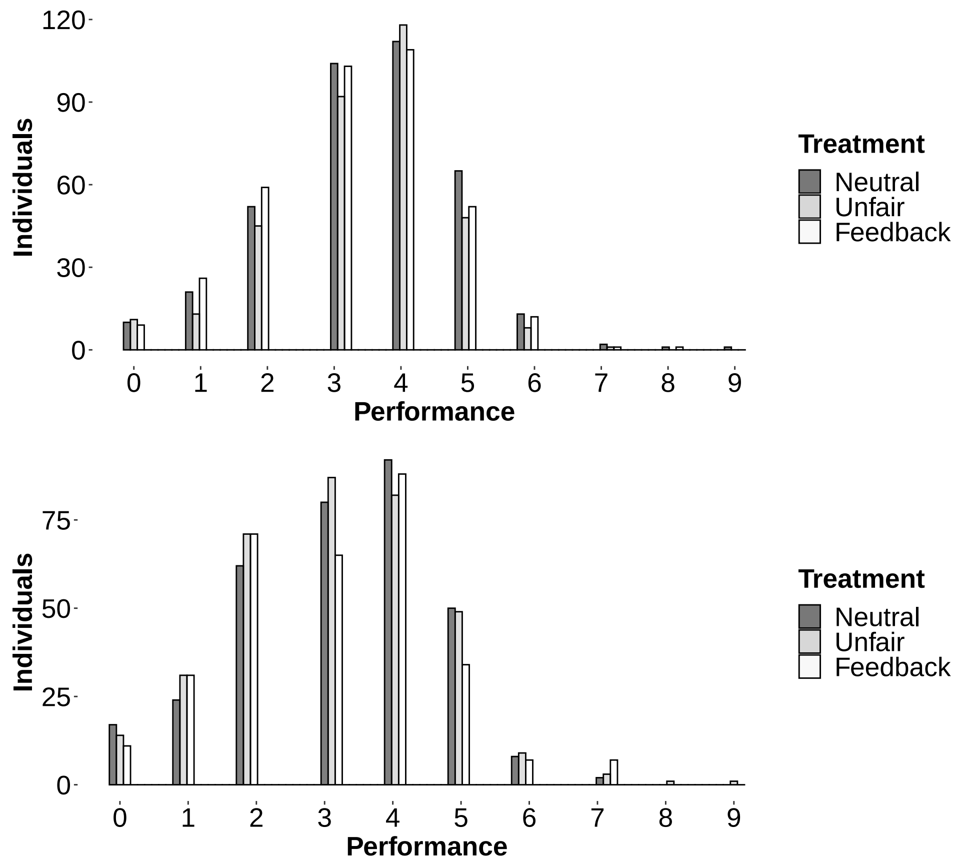


Table 6: Sample Size by Gender and Treatment

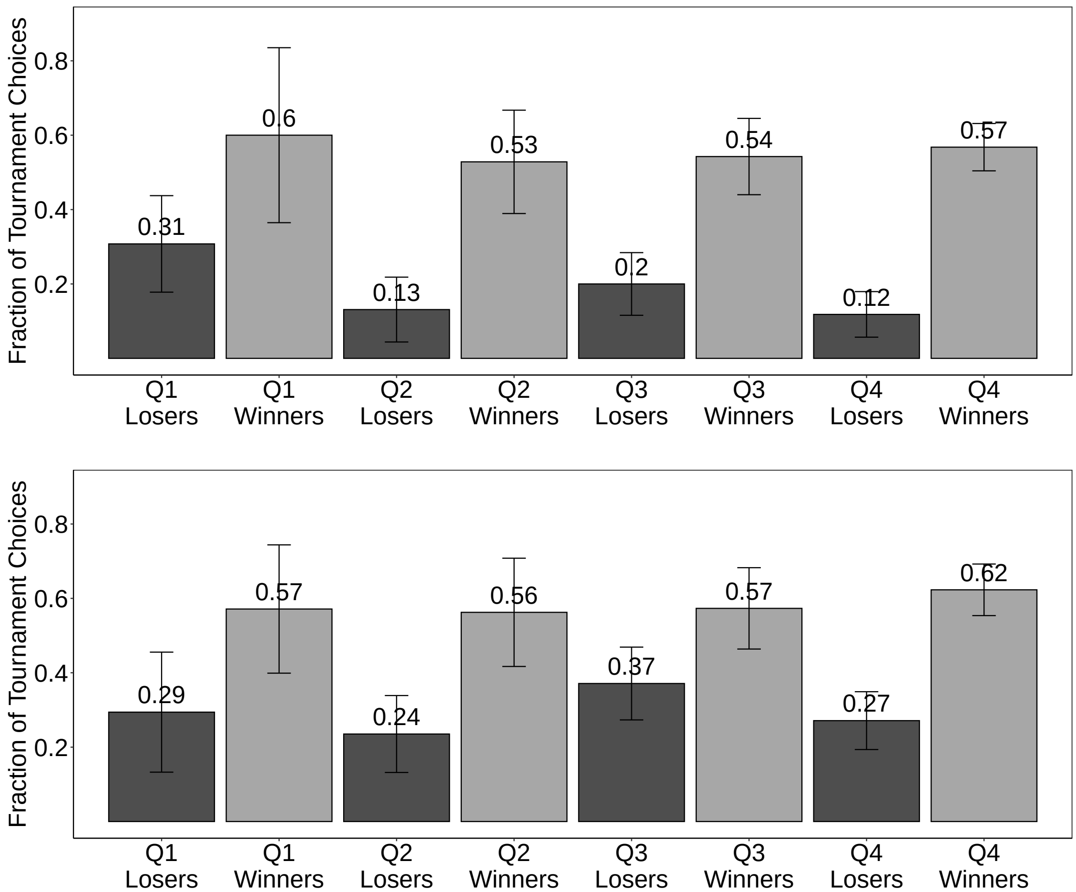
Gender	Treatment	N.	Freq.	N.lost	Freq.lost
Female	Neutral	381	0.350	155	0.407
Female	Unfair	336	0.309	152	0.452
Female	Feedback	372	0.342	155	0.417
Male	Neutral	335	0.336	158	0.472
Male	Unfair	348	0.349	176	0.506
Male	Feedback	314	0.315	150	0.478

Notes. The table presents the number of participants of each gender in each treatment. The frequencies (Freq.) represent the share of each gender assigned to a given treatment. N.lost is the number of participants who lost in Stage 2. Freq.lost is the fraction of participants in each category who lost in Stage 2.

D Additional Results

D.1 Performance Analysis

Figure 6: Tournament Entry Decisions by Performance Quartile



Notes. This figure plots the fraction of participants choosing to enter the tournament in Stage 3 by performance quartiles (Q1-Q4), Stage 2 Outcome (black: losers, grey: winners) and Treatment (top: Neutral, bottom: Unfair). Error bars represent 95% confidence intervals.

Table 7: Tournament Entry Regressions with Additional Controls

	Coefficient (Std. Errors)		
	Neutral	Unfair	Feedback
	(1)	(2)	(3)
	Dep Var: Tournament Entry		
(a) Female	−0.025	−0.098*	−0.057
	(0.043)	(0.055)	(0.050)
(b) Winner	0.434***	0.338***	0.032
	(0.049)	(0.084)	(0.059)
(c) Winner*Female	−0.071	0.111	0.127
	(0.066)	(0.093)	(0.107)
(d) Deserved to Win		0.103	0.406***
		(0.068)	(0.060)
(e) Deserved to Win*Female		−0.134	−0.140*
		(0.091)	(0.082)
Age	0.005		
	(0.019)		
Sport		0.091*	
		(0.052)	
Number of male siblings			0.075**
			(0.037)
Winner*Age	−0.076**		
	(0.031)		
Winner*Sport		−0.190**	
		(0.075)	
Winner*Number of male siblings			−0.115***
			(0.036)
Constant	0.293**	0.382***	0.367**
	(0.090)	(0.110)	(0.114)
	Effects for Women		
Winner (b+c)	0.363***	0.449***	0.159***
Deserving Winner (d+e)		-0.031	0.266***
Stage 1 Score Fixed Effects	Yes	Yes	Yes
Observations	716	684	686
Adj. R^2	0.170	0.111	0.186

Notes. This table replicates the analysis of Table 2 while incorporating the main predictor of the effect of losing in each treatment selected by machine learning. Non-binary variables are normalized so that a one-unit change represents one standard deviation. See the notes to Table 2 for more information.
*** p<0.01, ** p<0.05, * p<0.1.

E Instructions

Figure 7: Stage 1 Introduction and General Instructions common to all Treatments

Thank you for participating in our study. It will take about 15 minutes to complete.

You will receive £1.50 ($2.00) for completing the study. In addition to that, you can earn **a bonus of up to £3.50 ($4.50).** The average bonus is around £1.20 ($1.50).

You will not receive the full show up fee if you do not pass some comprehension questions.

The information in this survey is truthful and accurate. In particular, the decisions you make are real and any bonus payments you earn will be sent to you through Prolific in the next few business days.

Your data will be completely anonymous and only be used for research purposes. By clicking the button below you will automatically allow us to do so.

We will now go through the instructions. Please read them carefully. **You are only eligible for a bonus payment if you adhere to the instructions.**

If you have any questions or concerns please contact Stefano Piasenti at spiasenti@diw.de

Please click the button below to continue (if you do not see it yet, it will appear soon).

Please check the box below to proceed.

I'm not a robot

reCAPTCHA
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In this study, you will be asked to complete three main tasks, named **Task 1**, **Task 2** and **Task 3**, respectively.

At the end of the study we will randomly select one of the tasks by randomly drawing a number between 1 and 3. This task will be the one that counts for your final payment.

The method used to determine your payment varies across the three tasks. Before each task, we will describe in detail how your payment is determined.

Please click the button below to continue (if you do not see it yet, it will appear soon).

Figure 8: Stage 1 Piece Rate – Instructions for Stage 1 common to all Treatments

Instructions for Task 1

For Task 1, you will be asked to solve a series of problems by counting the number of zeros (0) in tables consisting of zeros (0) and ones (1). You will be given 90 seconds to count the zeros (0) in as many tables as possible.

Here is an example of what a table looks like (the correct answer is 36):

1	1	1	1	0	0	0	1
1	0	1	0	1	1	0	0
0	1	0	0	0	0	0	0
1	1	1	1	1	0	0	0
1	0	1	0	1	0	0	0
1	0	1	0	0	0	0	0
1	0	1	1	1	0	1	0
1	0	0	0	0	1	0	1

In Task 1, you receive £0.15 per table you solve correctly during the 90 seconds. You receive no money for tables you are unable to solve, or for which you provide an incorrect solution.

After the 90 seconds are up, you will automatically continue to the next page. That means that you do not need to keep time yourself, but can concentrate on solving the tables. If you solve all available tables before the time is up, please just wait for the survey to continue automatically.

We refer to this task as the **"Piece Rate Task"**.

Figure 9: Stage 1 Comprehension Questions common to all Treatments

Comprehension questions

To make sure the instructions are clear enough, please answer the following questions. You may scroll up to re-read the instructions if you do not remember the answer.

Note that you will not be able to proceed with the survey if you fail to answer all questions correctly after your *second* try.

Question 1

What is the activity in Task 1?

- ○ Adding up numbers
- ○ Counting zeros
- ○ Solving CAPTCHAs
- ○ Counting ones

Question 2

Is the following statement true or false?

"In Task 1 you receive £0.15 per table you solve correctly during the 90 seconds."

- ○ False
- ○ True

Question 3

What happens after the 90 seconds are up?

- ○ You will automatically continue to the next page
- ○ You will have to perform the task again
- ○ The study finishes

Now you will proceed with the actual task.

Please click the button below to start with Task 1.

Figure 10: Stage 1 Solve Tables (counting task) for 90 Seconds with Piece Rate Incentives and Feedback on Score common to all Treatments

1. Please count the number of 0s in the table below.

1	1	0	1	0	1	0	0
1	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0
0	0	0	0	0	1	0	0
1	0	0	1	1	0	0	0
0	0	1	0	0	1	0	0
1	1	0	0	0	0	0	0
0	0	1	1	1	0	1	1

number of 0s:

You scored correct answers.

Please click to continue.

You have completed Task 1. Please click to continue to the instructions for Task 2.

Figure 11: Stage 2 Tournament – Different Instructions for Task 2 in Neutral versus Unfair/Feedback Treatments

Instructions for Task 2

As in Task 1, you are asked to count the number of zeros (0) in tables consisting of zeros (0) and ones (1). You will be given 90 seconds to count the zeros (0) in as many tables as possible.

The difference is that in Task 2 you will take part in a tournament. In particular, your performance will be compared to that of another participant, who has already completed the task.

NEUTRAL TREATMENT

In particular, if your score (that is, the number of solved tables) is higher than that of your opponent, you will receive £0.30 per table you solve correctly. You receive £0.00 for this task if your score is lower than that of your opponent. In case of a tie, it will be determined by a virtual coin flip whether you receive £0.30 per table you solve correctly or £0.00.

UNFAIR/FEEDBACK TREATMENT

Whether you win the tournament will depend on your score, your opponent´s score, and chance. In particular, 75% of the time you win the tournament if your score is higher than your opponent´s score. We refer to this case as the **best-score-wins** case.

The other 25% of the time, you will win the tournament if your score is *lower* than your opponent´s score. We refer to this case as the **worst-score-wins** case.

In case of a tie, it will be determined by a virtual coin flip whether your win or lose.

Regardless of which case applies, you will receive £0.30 per table you solve correctly if you win the tournament. If you lose the tournament you will receive £0.00 per table you solve correctly.

In other words, if your score is higher than your opponent´s score, there is a 75% chance that you win the tournament. However, there is also a 25% chance that you undeservedly lose it! After the task, you will find out whether your score exceeded your opponent´s and whether you won or lost the tournament.

After the 90 seconds are up, you will automatically continue to the next page. That means that you do not need to keep time yourself, but can concentrate on solving the tables. If you solve all available tables before the time is up, please just wait for the survey to continue automatically.

We refer to this task as the **"Tournament Task".**

Figure 12: Stage 2 Comprehension Questions – Different Questions for Task 2 in Neutral versus Unfair/Feedback Treatments

Comprehension questions

To make sure the instructions are clear enough, please answer the following questions. You may scroll up to re-read the instructions if you do not remember the answer.

NEUTRAL TREATMENT

Question 1

Is the following statement true or false?

In Task 2 you are asked to count the zeros (0) in a series of tables like in the previous task.

- ○ False
- ○ True

Question 2

Which of the following statements is the correct one?

- ○ You will earn £0.30 per table you solve correctly in any case
- ○ You will earn £0.30 per table you solve correctly only if your score is higher than that of your opponent
- ○ You will earn £0.15 per table you solve correctly

UNFAIR/FEEDBACK TREATMENT

Question 1

Which of the following statements is the correct one?

- ○ There is 25% chance that you lose the tournament even if your score exceeds the score of your opponent
- ○ If your score exceeds the score of your opponent you will always win the tournament
- ○ If your score exceeds the score of your opponent you will always lose the tournament

Question 2

Which of the following statements is the correct one?

- ○ Task 1 and Task 2 are identical
- ○ In Task 2 your performance will be compared to that of another participant, who has already completed the task.
- ○ You will earn £0.15 per table you solve correctly

Figure 13: Stage 2 Solve Tables (counting task) for 90 Seconds with Tournament Incentives

1. Please count the number of 0s in the table below.

1	1	0	1	0	1	0	0
1	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0
0	0	0	0	0	1	0	0
1	0	0	1	1	0	0	0
0	0	1	0	0	1	0	0
1	1	0	0	0	0	0	0
0	0	1	1	1	0	1	1

number of 0s:

Figure 14: Stage 2 Rank (belief) Elicitation Task common to all Treatments

Before moving on to the next part of the experiment, we would like you to **guess how your score in Task 2 compares to 100 previous participants.**

In particular, we ask you to **guess your rank.**

We calculate your rank by comparing your score to the one of 100 other participants who already played Task 2. In case there are ties, the average rank will be used.

Your guess can range from 1 (better than everyone else) to 101 (worse than everyone else). You will receive a base payment of £0.50, with a penalty of £0.02 times the absolute difference between your true rank and the stated (guessed) rank.

This means that you will receive £0.50 if your guess is exactly correct and you will receive £0.00 if your guess is off by 25 or more. In other words, the more accurate your guess is, the higher your payment!

Now, please guess your rank in Task 2 compared to 100 previous participants. **Please choose a value between**

1 (you believe your were the BEST)

and

101 (you believe you were the WORST):

Figure 15: Stage 2 Feedback on Score for Neutral/Unfair versus Feedback Treatment

NEUTRAL/UNFAIR TREATMENT

You scored correct answers.

You won in the tournament in Task 2.

FEEDBACK TREATMENT

You scored correct answers.

Your actual rank compared to 100 other participants in Task 2 was:

You scored less correct answers than your opponent. therefore, you deservedly lost in the tournament in Task 2.

Figure 16: Stage 2 Updating the Rank (belief) Elicitation Task in Neutral and Unfair Treatments

Before moving on to Task 3, you have the opportunity to update your estimated rank based on the outcome of the "Tournament Task" you see above.

UNFAIR TREATMENT

Remember that you won in the tournament in Task 2. There was 75% chance that you lost deservedly and 25% that you lost undeservedly.

Note that your updated estimated rank will overrule your previous estimate.

Your previous estimate:

Please enter your new estimate here by choosing a value between

1 (you believe you were the BEST)

and

101 (you believe you were the WORST):

Figure 17: Stage 3 Choice – Instructions for Stage 3 common to all Treatments

Instructions for Task 3

Like the previous two tasks, you will be given 90 seconds to count the zeros (0) in a series of tables with ones (1) and zeroes (0).

The difference is that, in Task 3, you will get to choose which of the two previous payment schemes you would prefer to apply to your score.

In Task 3 your earnings are determined as follows:

- If you choose the **"Piece Rate"**, you will receive £0.15 per table you solve correctly.
- If you choose the **"Tournament Rate**", your performance will be compared to the score of another participant who already played the task (not the same one as in Task 2). If you solve more tables in Task 3 than your opponent, you will receive £0.30 per table you solve correctly. You will receive £0.00 if you solve fewer tables than your opponent. Any ties are broken using a virtual coin flip.

The next screen will ask you to choose whether you want the "Piece Rate" or the "Tournament Rate" applied to your score in Task 3.

You will then be given 90 seconds to count the number of zeros (0), in the same way as before.

Figure 18: Stage 3 Comprehension Questions common to all Treatments

Comprehension questions

To make sure the instructions are clear enough, please answer the following questions. You may scroll up to re-read the instructions if you do not remember the answer.

Question 1

Which of the following statements is the correct one?

- ○ In Task 3 you will be paid according to the "Piece Rate" payment scheme
- ○ In Task 3 you can choose which payment scheme you would prefer to apply to your score
- ○ In Task 3 you will be paid according to the "Tournament Rate" payment scheme

Question 2

Is the following statement true or false?

In Task 3 you are asked to count the zeros (0) in a series of tables like in the previous two tasks.

- ○ True
- ○ False

Figure 19: Stage 3 Solve Tables (counting task) for 90 Seconds with Piece Rate or Tournament Incentives

1. Please count the number of 0s in the table below.

1	1	0	1	0	1	0	0
1	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0
0	0	0	0	0	1	0	0
1	0	0	1	1	0	0	0
0	0	1	0	0	1	0	0
1	1	0	0	0	0	0	0
0	0	1	1	1	0	1	1

number of 0s:

Figure 20: Stage 3 Feedback in all Treatments if Piece Rate was Chosen

You scored correct answers.

Please click to continue.

Figure 21: Stage 3 Feedback in all Treatments if Tournament was Chosen

You scored correct answers.

You won in the tournament in Task 3.

Please click to continue.

Figure 22: Stage 3 Conclusive Message with Information about Payment and Final Questionnaire

The experiment is now over.

Before informing you about your final payment, we would like you to answer a short questionnaire. It will take about 5 minutes to complete.

Now click to continue to get started with the questionnaire.

Figure 23: Example of Randomly Selected Stage for Payment after Finishing the Questionnaire

The task which has been randomly drawn for payment is Task 2.

You scored ... . You won, therefore your payment for the task is:

... **£**

Your actual rank compared to 100 previous participants was:

... **rank**

Your guess was:

... **guess**

Therefore, the payment for your guess is:

... **£**

Your final payment (excluding £1.50 fixed fee) is:

... **£**

Please click the button below to continue.

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Does Unfairness Hurt Women? The Effects of Losing Unfair Competitions

Abstract

How do men and women differ in their persistence after experiencing failure in a competitive environment? We tackle this question by combining a large online experiment (N=2,086) with machine learning. We find that when losing is unequivocally due to merit, both men and women exhibit a significant decrease in subsequent tournament entry. However, when the prior tournament is unfair, i.e., a loss is no longer necessarily based on merit, women are more discouraged than men. These results suggest that transparent meritocratic criteria may play a key role in preventing women from falling behind after experiencing a loss.

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