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## Effect of social information on competition choice

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## ABSTRACT

We examine how social information about competition choices influences individuals' willingness to compete. Participants perform a real-effort task under both piece-rate and tournament incentives, and subsequently make competition choices in two rounds. Between rounds, we exogenously vary the information provided about others' choices across three treatments. We find that social information about the proportion of participants who chose to compete in the first round significantly affects the willingness to compete in the second round. This effect is not driven by the salience of the incentive schemes. Observing a lower rate of competition among peers increases an individual's propensity to enter the tournament. This evidence is consistent with predictions from a rational model of Bayesian learning, in which individuals strategically choose to compete based on their treatment-induced belief about the average ability of other participants.

## 1. Introduction

An important hallmark of most modern organizations is that candidates are evaluated and promoted through a competitive process. These career events require prospective candidates to compete against each other. In such events, individuals often decide how much to compete by observing their peers. For instance, colleagues may infer each other's competitiveness through casual conversations or simply by observing their past behavior. Besides, organizations may have policies where the pool of employees competing for a promotion is public information. Further, in professional portals, such as LinkedIn, individuals are more likely to complete a job application when they can see how many others have applied (Gee, 2019). This suggests that information about peers' choice to compete can shape one's own competitive strategy. For example, if individual A knows that colleague B is applying for a project lead role, is A more likely to compete for the same position, or wait for a future opportunity? If information, about others' choices, affects one's competitive behavior, this can have implications for how selection and promotion processes are structured within organizations.

In this paper, we study how informing participants about the competition choice of their peers affects their own decision to compete. We design a real-effort experiment in which participants choose between a non-competitive (piece-rate) and a competitive

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(tournament) payment scheme, twice. Prior to the second-round choice, participants receive information about their peers' competition decisions in the first round. By systematically varying the content of this social information across treatments, we examine whether and how peer choices shape individuals' willingness to enter competition. Importantly, the participants in our experiment are MBA students at one of India's top business schools, admitted through a highly competitive selection process.

Decision-making in our study is in a setting characterized by uncertainty about peers' types. In such environments, the provision of social information can influence competitive choices through two distinct channels. The first is the strategic response channel, grounded in standard economic theory, which emphasizes best-response functions. When individuals' best responses are decreasing in the actions of others, theory predicts that behavior is shaped by signals about others' choices. For instance, if agents receive information suggesting low (high) average competition, they may update their beliefs about their chances of winning upward (downward) and, as a result, be more (less) inclined to compete. The second channel operates through social learning and predicts that individuals tend to emulate the observed behavior of peers (Bikhchandani et al., 1998; Fatas et al., 2018). If the information reveals that a greater (smaller) proportion of others are choosing to compete, this may trigger behavioral contagion or peer effects, leading individuals to conform by also competing more (less). The strategic adjustment channel and the conformity-based social learning channel thus predict opposing behavioral responses. Using an experimental approach, our study sheds empirical light on the causal relationship between social information and the willingness to compete, and identifies which of the two effects, strategic or conformist, dominates in practice.

Providing individuals with any information can also increase the salience of certain actions. For instance, learning about peers' decisions to compete may render that choice more noticeable, memorable, or prominent, making it more likely to be processed and retained (see Bordalo et al., 2022 for a review on salience). As a result, any observed treatment effects could arise from the heightened attention due to salience, rather than from social information per se. Our experimental design allows us to separate out these effects and explicitly test for the role of salience.

The predominant indicator of willingness to compete typically revolves around selecting between a piece-rate compensation and a tournament scheme (Niederle and Vesterlund, 2007), as methods of payment for task completion. This measure of competitiveness has been shown to be pivotal in understanding individuals' economic outcomes (see Niederle 2017 for a review). For instance, it significantly predicts educational choices such as academic track and stream choices, where more competitive students gravitate towards STEM-related fields of study (Buser et al., 2014, 2017, 2021). Further, in the labor market, competitive individuals are found to earn more than their less competitive peers, and are also more likely to work in high-paying industries (Reuben et al., 2015).

In our study, individuals participate in an experiment with multiple rounds. Following the piece-rate and tournament incentive payment tasks, they face two choice-based tasks: the baseline task and the endline task. In both baseline and endline tasks, participants are asked to choose between the two payment schemes. In the control condition, participants receive no effective information between the baseline and endline tasks; the information presented before the endline task is generic and does not have any explicit information about the tournament choice of peers. In contrast, in the treatment conditions, the participants are provided with some information about the tournament entry choices of their peers in the session. We vary the content of this information across two treatment conditions. In the *Average* treatment, they are informed about the percentage of participants in the session who chose tournament in the baseline round. A comparison of endline and the baseline tasks in the *Average* treatment condition relative to that in the control condition allows us to infer whether social information impacts competition choice in the endline round. Correspondingly, in the *Random* treatment, participants are informed about the choice made by a randomly chosen player from the session, which can either be piece rate or tournament.

To better understand the effects of our information treatments on tournament entry and the channels through which these effects may operate, we develop a strategic model of competition choice when social information is provided. In our model, agents can be either of high or low ability. In addition, similar to the control condition in our experiment, they are not aware of the competition choice of others, and hence, form beliefs about the overall competition before making their choice between piece-rate or tournament. The model shows that, high ability agents find it more profitable to compete than the low ability ones, and hence, a larger proportion of high ability agents choose competition in equilibrium. Since high ability agents are more likely to select into tournaments in equilibrium, beliefs about competition serve as beliefs about the underlying ability distribution, with higher expected competition reflecting a stronger pool of potential competitors.

Since beliefs about competition reflect beliefs about opponent strength, the model predicts that agents behave strategically when they are provided with information about average competition levels (*Average*). When average competition is low, agents infer that the pool of participants is likely of lower average ability, and hence, update their perceived chances of winning upwards, leading them to compete more. Similarly, higher average competition signals a stronger competitive environment, in turn reducing their perceived chances of success and hence lowering entry into tournaments. In contrast, we show that the agents do not update their beliefs much when they are made aware of the competition choice of a randomly chosen agent (*Random*). This is because the information about one random individual is not sufficiently strong, compared to information about the average, to induce shifts in beliefs or affect competition choice.

As mentioned above, in the *Average* treatment, a decision-maker may respond to the information provided by rationally updating her beliefs (as our theoretical model predicts), conform to the information about peers, or she may simply be influenced by the salience of the information itself. For instance, in our setting, the subjects could be responding to the 'percentage of participants choosing

tournament', a form of social information (strategic or conformist) or the increased prominence of the 'tournament payment scheme' made salient by the treatment.<sup>1</sup> While the preferred interpretation in the literature is that the social information channel is at work, the salience channel remains a plausible confound, which extant research has largely been silent about. Our experimental design helps disentangle these two effects. Specifically, in our *Random* treatment, salience is preserved, but no aggregate social information is conveyed. Participants are simply told that a randomly selected participant chose the tournament payment scheme.<sup>2</sup> If salience is the primary mechanism driving the choices in the *Average* treatment, then the *Random* treatment should yield a similar effect as the *Average* treatment, when compared to the control. If not, social information is the more likely explanation for the observed choices in the *Average* treatment.

Our experimental results show that in the *Average* treatment, the information about the percentage of participants choosing competition in a previous round significantly increases the likelihood of subjects choosing competition. However, the information about the competition choice of a randomly chosen subject does not have any effect. These results are consistent with the predictions of our theoretical model. This indicates that the subjects respond to the information conveying the proportion choosing competition, and not the salience of the tournament scheme in the message. Further, using the variation in the information within the treatment groups across sessions, we find that information conveying a low proportion (below 40 percent) of others choosing tournament, is more likely to induce subjects to choose competition. Thus, we find that the effect of social information on willingness to compete is in the opposite direction to what we would expect under conformity. We do not observe any such pattern in the *Random* treatment, information about a randomly selected participant has no significant effect on individuals' subsequent choices.

Our paper makes four main contributions to the literature. First, there is a large literature examining the effect of social information on economic decisions, including charitable giving (Frey and Meier, 2004; Croson and Shang, 2008, 2009; Krupka and Weber, 2009; S. Smith et al., 2015); social dilemmas (Noussair and Tucker, 2007; Cason et al., 2016; Delaney and Jacobson, 2016; Brent et al., 2019; Dimant, 2019); environmentally responsible behavior (Allcott, 2011; Ferraro et al., 2011; Ferraro and Price, 2013; Allcott and Rogers, 2014; Brent et al., 2015); risky behavior (Helfinstein et al., 2014; Tomova and Pessoa, 2018), and unethical behavior (Innes and Mitra, 2013). In these studies, social information offers a signal about the prevailing social norm (Cialdini, 2003) or a focal point and affects behavior through pro-social concerns. Individual behavior can also be influenced by observing other's behavior through social learning (Banerjee, 1992; Shiller, 1995). The decision to choose competition, like most decisions, can also be shaped by social learning. For instance, competitiveness has been shown to be influenced by cultural and societal norms (Gneezy et al., 2009), family background (Almås et al., 2015), and successful role models (Alan and Ertac, 2019). In most of these cases, the effect of social information goes in the direction of conformity. However, there are some exceptions. For example, in the literature on contests (Tullock, 1980), studies have shown that disclosing the number of competitors can reduce entry (Boosey et al., 2020; Fu and Wu, 2022; Jiao et al., 2022; Chernulich et al., 2023). While previous research has investigated how feedback on individual and relative performance affects tournament entry (e.g., Ertac and Szentes, 2011; Wozniak et al., 2014; Berlin and Dargnies, 2016), little attention has been paid to the role of social information itself and the underlying mechanisms through which it shapes competitive behavior. Our paper addresses this research question and shows that individuals respond to treatment-induced beliefs formed through exposure to social information. Importantly, rather than simply conforming to others' choices, individuals behave strategically: when they observe lower average competition, they update their beliefs about their chances of winning upward, leading to greater entry into competition.

Second, the literature on social information often fails to disentangle the instrumental role of information from its salience effect. For instance, revealing information about other donors' behavior can increase donations either by signaling what an appropriate donation is, or by making higher donations more salient (Croson and Shang, 2008). There is a rich literature in psychology that studies the role of salience in decision-making (see, for example, Taylor and Thompson, 1982). This literature broadly proposes that a stimulus, such as information, can automatically and involuntarily attract a decision maker's attention, in accordance with 'what you see is all that is' principle (Kahneman, 2011). The literature that studies the effect of salience on economic behavior is recent, but growing (Bordalo et al., 2022) and shows that salience helps allocate scarce cognitive resources efficiently and, therefore, affects choices in the context of risk (Bordalo et al., 2012; Nielsen et al., 2025), consumer choice (Bordalo et al., 2013b), asset prices (Bordalo et al., 2013a), and memory (Bordalo et al., 2016). In our setting, it is plausible that limited cognitive resources induce people to choose a certain payment choice based on what is salient. Our experiment allows us to test for the salience effect and we show that we can rule out salience as the channel through which social information in competition choice operates.

Third, we contribute to the literature that aims to understand the roots of competitiveness. This literature has focused mainly on gender, (see Bertrand, 2011 and Niederle and Vesterlund, 2011, for review) and sometimes on other social markers such as caste (Banerjee et al., 2018). Interventions such as training programs (Alan and Ertac, 2019; Almås et al., 2020), information about competitor's gender (Datta Gupta et al., 2013), advising on potential earnings implications (Kessel et al., 2021), and providing feedback on performance (Ertac and Szentes, 2011) have been shown to affect competition choice. However, the strategic aspects of how information about others' behavior affects competition choice is largely understudied. Our research shows that the decision to compete is, in part, strategically determined.

Finally, our paper contributes to a growing literature examining how belief updating shapes entry into competitive environments.

<sup>1</sup> The participants in the *Average* treatment are shown the information as: "The percentage of subjects who chose Rule-100 in Task 3 is 'X' %". The tournament payment scheme is referred to as Rule-100 in the experiment.

<sup>2</sup> Participants in the *Random* treatment are shown the following information: "One randomly chosen participant chose Rule 'Y' in Task 3". Rule 'Y' is either Rule-100 or Rule-25 whichever is drawn during the session. The tournament payment scheme is referred to as Rule-100 and the piece rate as Rule-25 in the experiment. The screenshots are provided in Figure B2 in Appendix B.

Most papers in this literature study how individuals update beliefs about their own performance or relative ability, and how these beliefs affect competition choices (Ertac and Szentes, 2011; Wozniak et al., 2014; Möbius et al., 2022). In these settings, participants typically receive performance feedback or signals about their own outcomes and revise beliefs about their ability, which in turn influences their willingness to compete. In contrast, we develop a framework in which individuals update beliefs about the overall competitive environment. In our setting, social information about others' tournament choices serves as a signal of opponent strength, and individuals adjust competition entry based on inferred competitiveness rather than direct feedback about their own performance. Our results, therefore, show that entry decisions are shaped not only by beliefs about one's own ability, but also by beliefs about the strength of the competitive environment inferred from others' behavior.

The rest of the paper is organized as follows: Section 2 discusses the experimental design and procedure. Section 3 presents a rational model of competition choice and its theoretical predictions. Sections 4 and 5 present our findings, including those related to heterogeneous treatment effects, while Section 6 discusses these results and concludes.

## 2. Experimental design

Our research strategy involved a controlled laboratory experiment conducted using monitored Zoom sessions.<sup>3</sup> At the beginning of the session, participants are informed that they will be required to complete six tasks, and one of them will be randomly chosen at the end of the session to determine their payment. Instructions for each task appear sequentially, immediately after the preceding task. The first three tasks and the sixth one involve a real effort task, which measures performance, beliefs about performance, and willingness to compete. The fourth and fifth tasks are related to incentivized elicitation of willingness to cooperate and risk preferences, respectively. At the end of the experiment, we collected participants' demographic information. The complete experimental instructions are provided in Appendix C.

### 2.1. Experimental tasks

Our measure of willingness to compete closely follows the design of Niederle & Vesterlund (2007). Before the tasks begin, subjects are randomly assigned to fixed groups of four. The assignment process was independent of gender. They do not know the identity of the others in the group, who remain anonymous throughout the experiment. In each of Tasks 1, 2, 3, and 6, a subject is provided with a series of simple arithmetic problems, each based on two matrices.

#### *The matrix problems*

The subjects are presented with two  $3 \times 3$  matrices, side by side on the screen, and are required to pick the smallest numbers from each matrix, add the two smallest numbers, and enter the sum in the space provided.<sup>4</sup> They are presented with a maximum of 30 such matrices, one after the other, and must solve as many as possible in 90 s. The score for each task is decided by the number of correct answers entered. An example of the task can be found in Fig. B1 in Appendix B.

#### *Tasks 1 – 3, 6*

In Task 1, subjects complete the matrix problems under the piece-rate compensation scheme, and they are paid 25 Indian Rupees (INR) for every correct answer.<sup>5</sup> We refer to this payment scheme as Rule-25 for convenience. In Task 2, they are paid under the tournament compensation scheme, where the subject scoring the highest in their group of four receives 100 INR for each correct response, while the remaining members receive zero. In the event of a tie, the winner is chosen at random. We denote this payment rule as Rule-100.

In Task 3, the baseline task, subjects choose the payment rule before commencing the addition task. Subjects choosing Rule-25 (piece-rate) are paid 25 INR for every correct answer. For subjects choosing Rule-100 (tournament), their scores in Task 3 are compared to the scores of group members in Task 2 and they are paid 100 INR for every correct answer if their score exceeds the scores of other group members in Task 2, zero otherwise. Participants are explicitly informed about the comparison of Task 3 performance to Task 2 performance, and that their choice in Task 3 does not affect the payoffs of other participants in that task, ensuring that their payment choice is not influenced by other-regarding preferences. After completing the addition task under both the payment schemes in Task 1 and 2, the choice between the two payment schemes in Task 3 gives us the baseline measure of willingness to compete.

Task 6, the second choice round or the endline task, records our main outcome of interest, the choice of payment rule. First, the subjects are given specific information about the choices of the subjects in Task 3. This information is varied between the treatment groups and reported on the display screen. After that, their preferred payment rule is recorded, following which they begin the matrix problem task. As in Task 3, their performance in this task is compared with that in Task 2. The nature of information provided and its variation between the treatment groups is discussed in the next sub-section.

In each of the Tasks 1, 2, 3, and 6, we collect information on subjects' beliefs about the number of matrices they expect to solve correctly (absolute performance) before the task. At the end of each task, we also elicit subjects' beliefs about their relative performance (their perceived rank within the group of four) and the probability of winning (i.e., being the top performer in the group),

<sup>3</sup> The experimental sessions were conducted during the COVID-19 pandemic. Details of the implementation are discussed in Section 2.3.

<sup>4</sup> The task is a variant of the real effort task used in Buser et al. (2024).

<sup>5</sup> Under Purchasing Power Parity terms, 100 INR was approximately equivalent to USD 4.72 at the time of the experiment.

reported as a percentage between 0 and 100.<sup>6</sup> Subjects receive a bonus of 50 INR if their reported belief exactly matches the realized outcome (actual number of matrices solved or rank within the group). For the reported probability of winning, a bonus ranging from 0 to 50 INR is awarded using a quadratic scoring rule. These reported beliefs were paid if the corresponding tasks were randomly chosen for payment.

#### Task 4

In Task 4, subjects participate in a linear public good game implemented as a binary voluntary contribution mechanism in groups of four. Each participant receives an endowment of Rs. 150 and chooses between a private account (Project B) and a group account (Project A). A contribution to the group account increases each group member's earnings by Rs. 75, implying a marginal per capita return (MPCR) of 0.5 (75/150). Choosing the private account yields a private return of Rs. 150, with no effect on the earnings of other group members. Payoffs are linear in the total number of contributors, creating a standard social dilemma in which contributing is socially efficient but privately costly. This gives us a measure of their prosocial behavior.

#### Task 5

In Task 5, we measure risk preferences using a design based on Holt & Laury (2002). The subjects make a series of 16 choices between a lottery with an expected value of INR 200 and certain amounts that ranged from INR 20 to INR 320. These choices are used to determine the risk aversion coefficient, assuming a CRRA utility function.

A couple of design features are worth noting. First, we deliberately included these two tasks between Task 3 and Task 6, where our main outcomes of interest are recorded, to mitigate demand effect, if any. Without these intervening tasks, participants would make consecutive tournament entry decisions, with the second decision in the treatment condition immediately following the provision of additional information. This close sequencing could heighten the experimental manipulation, potentially inducing them to adjust their behavior in response to perceived expectations rather than reveal their underlying preferences. The filler tasks (Tasks 4 and 5) introduce temporal and cognitive separation between the two decisions and help ensure that the second decision is less influenced by participants' views of the researcher's expectations. At the same time, they give us useful diagnostic measures for preferences relating to cooperation and risk, which we use in our regression analysis.<sup>7</sup> Second, we do not offer feedback about either the performance or the earnings at the end of each task. This prevents anchoring effects and helps maintain decision independence across tasks.

## 2.2. Treatments

**Control** – For the subjects in the control group, the following information was displayed: "**Some subjects chose Rule-100 while others chose Rule-25.**" Clearly, the above statement does not provide the subject with any credible signal regarding the choice of other subjects in Task 3 of the experiment, and therefore, does not have any information value, and hence, provides us with an appropriate counterfactual using which *Average* and *Random* treatments can be compared.

**Average Treatment** – In this treatment, the subjects are provided information about the proportion of subjects who chose Rule-100 in Task 3. The following information is displayed: "**The percentage of subjects who chose Rule-100 in Task 3 is 'X' %.**"<sup>8</sup> The value of the variable 'X' is based on the actual proportion of subjects choosing Rule-100 in Task 3 of the session in which the experiment was conducted. With the sessions run over Zoom, the number of participants in a session was implicitly public information. This is an important feature of our design. The information about the proportion who chooses Rule-100 allows subjects to update their beliefs about the overall competition, influencing their subsequent choices between Rule-25 and Rule-100 in Task 6. By comparing the within-subject choices in this treatment with the control treatment, we can identify how social information affects the choice of the payment incentive.

Note that, 'X' was different between sessions and was the same for all the subjects in a session. Across 7 sessions, 'X' ranged from 27 % to 55 %, with the number of participants per session varying between 30 and 60. While our main objective is to estimate the treatment effect, the variation in X across the sessions offers additional insight. It allows us to investigate whether the estimated treatment effect arises from sessions with low average competition choice or from those with high levels of competition choice. Further, an alternate design would have entailed providing information about high and low levels of competition from selected groups in prior sessions. However, since our aim was to signal competition choices of other participants, we chose to provide information from the same session.

**Random Treatment** – In this treatment, subjects are informed: "**One randomly chosen participant chose Rule 'Y' in Task 3.**" Rule 'Y' could refer to either Rule-100 or Rule-25 depending on the actual choice of a randomly chosen subject from the session. As in the case of *Average Treatment*, the value of Rule-'Y' varied across sessions but remains constant within each session. This treatment, when

<sup>6</sup> Eliciting beliefs about absolute performance before the task may itself affect payment choices. Although the elicitation procedure was identical across treatments, it could interact with treatment-specific information and serve as a cue that shifts subsequent decisions. This concern is partially mitigated by the fact that only beliefs about absolute performance were elicited pre-task; beliefs about relative performance, the margin that primarily drives the competition choice, were elicited afterward. We thank an anonymous referee for pointing this out.

<sup>7</sup> To isolate preferences for competition, we control for both pro-social behavior and risk preferences, following the literature that emphasizes the role of social preferences and risk attitudes in competitive behavior (Niederle & Vesterlund, 2007; Balafoutas et al., 2012).

<sup>8</sup> An alternate way of representing the same information would have been to report the percentage of subjects who chose Rule-25 in Task 3. This is simple for the participants to infer as the experimental instructions made it clear that participants had only two choices: Rule-25 or Rule-100.

compared to the control, allows us to test whether the salience of a payment rule alone influences competition choice. If such a comparison led to an effect similar to that observed in the *Average* treatment, then we can infer that salience is the dominant explanation. Otherwise, social information is the more likely explanation.

### 2.3. Sample and implementation

The experiment was programmed in oTree (Chen et al., 2016) and was conducted at the Indian Institute of Management Bangalore in India. The subjects were recruited from the first-year student cohort of the flagship two-year MBA program of the business school. Approximately 26 % of the subject pool is female, closely reflecting the program's overall gender composition. Importantly, the students in this program are selected through a highly competitive exam and are a cohort of high achievers.<sup>9</sup> They usually receive lucrative job offers after they graduate and go on to secure prominent leadership positions in the corporate sector. Notably, a majority (55 percent) of replications of Niederle & Vesterlund (2007) have been conducted with university students (Markowsky and Beblo, 2022), with some specifically involving MBA students (Cadsby et al., 2013; Reuben et al., 2015). As such, the subject pool in our study is well-suited to address the research question at hand.

The students in our sample joined the institute in the end of June 2020 and the experiment was conducted in the middle of July 2020. The experimenter explained the instruction screen-by-screen as the experiment progressed. One of the three treatments was randomly administered to subjects – thus, the randomization was conducted at the subject level within each session.<sup>10</sup> When the treatment-specific information was given, the experimenter simply asked the subjects to read the information they were provided on the screen. In total, there were 307 subjects across 7 sessions, of which 100 subjects participated in the *Control* treatment, 102 in the *Average* treatment, and 105 in the *Random* treatment. The individual level randomization employed by our design, allows us to detect an effect size of 0.13 with a power of 80 % and a significance criterion of  $\alpha = 0.05$ .<sup>11</sup>

This experiment was conducted at the peak of the COVID-19 pandemic. All academic activities at the institute were being conducted through Zoom, and so was this experiment. Participants were required to login to Zoom using their official university email IDs. In each session, participants were admitted into a Zoom meeting with their video and microphones turned off, to avoid spillovers from visual and auditory cues and to retain anonymity. They were not informed of the identities of other group members and therefore could not link decisions to specific individuals. Before each task, instructions were presented on the screen and read aloud by the experimenter to improve attention and focus throughout the session. At the end of the session, the subjects were informed about their payoffs. The subjects on average earned 420 INR (including participation fee) for a session that lasted for about an hour and fifteen minutes.

## 3. A model of strategic competition choice with social information

We now present a model of competition choice and examine how social information influences this choice, leading to two key testable hypotheses.

### 3.1. Environment

Consider  $N$  agents participating in the experiment. The ability of an individual, low ability ( $a_L$ ) or high ability ( $a_H$ ), with  $a_H > a_L$ , is private information and is not observable by others. For our baseline analysis, we assume that agents know their own ability and that this is common knowledge across agents. As discussed in Section 3.3, the model's qualitative predictions continue to hold when this assumption is relaxed. In the experiment, we can think of ability as the number of matrix problems an individual solves correctly. Everyone chooses between two reward schemes for their correct answers:

1. *Piece-rate*: Earn a fixed amount  $p$  for every correct answer, with the total payoff  $pa_i$ ,  $i \in \{L, H\}$ , depending solely on their ability to correctly solve the problems.
2. *Tournament*: Earn  $c > p$  for every correct answer only if they emerge as the winner of the tournament, else they earn zero.<sup>12</sup>

Thus, in a tournament, an individual's final payoff depends not only on their own ability, but also on their relative ability, captured by the total competition  $\theta$  and their belief about  $\theta$ . In our setup,  $\theta$  captures the overall competitiveness of the environment, reflected by the fraction of agents choosing to enter tournament. Suppose  $k$  agents choose to compete among  $N$  individuals, the realized tournament

<sup>9</sup> In 2021, out of 191,660 students who applied, only 0.26% were selected by this institute.

<sup>10</sup> Before Task 6 in the experiment, subjects view a different screen based on the treatment assigned. Information as specified in Section 2.2 is displayed on this screen. During the experiment, subjects are instructed to read the information carefully and make their choice. The screenshots are provided in Figure B2 in Appendix B.

<sup>11</sup> In the control group, the proportion of subjects choosing Rule-100 in Task 6, conditional on choosing Rule-25 or Rule-100, in Task 3, is 0.09 and 0.77, respectively (see Table A1 for details). Using these control proportions (0.09 and 0.77) and sample sizes of 100 in the control group and 100 in the treatment group, we obtain minimum detectable effects (MDEs) of 0.11 and 0.13 for 80 percent power at the 10 percent and 5 percent significance levels, respectively.

<sup>12</sup> In the experiment, each correct answer in a piece-rate earns 25 INR while the winner in a tournament earns 100 INR per correct answer, consistent with our assumption here.

entry rate is  $k/N$ .

Crucially,  $\theta$  apart from capturing the total competition, also serves as a proxy for the unobserved ability distribution of the agents. Since high ability agents solve more problems correctly ( $a_H > a_L$ ), they have a higher probability of winning against any randomly drawn opponent. As formally shown in [Proposition 1](#), high ability agents are therefore more likely to enter the competition compared to low ability agents. As a result, the total competition  $\theta$  is also informative about the underlying ability distribution, with a higher  $\theta$  signifying a larger proportion of high ability agents.

Individuals do not observe the total competition  $\theta$  when deciding on their payment scheme. Hence each agent forms a prior belief about  $\theta$ , where each agent's distribution of prior beliefs,  $F(\theta)$ , follows a *Beta* distribution with parameters  $\alpha$  and  $\beta$  given by

$$F(\theta) = \text{Beta}(\theta|\alpha, \beta) = \frac{\theta^{\alpha-1}(1 - \theta)^{\beta-1}}{B(\alpha, \beta)}$$

with  $B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$ ,  $\Gamma(\cdot)$  represents the *Gamma* function. Thus, we can think of each agent as having different  $\alpha$  and  $\beta$ , in turn determining their underlying belief about  $\theta$ . *Beta* distribution is commonly used to model prior distribution under Bayesian environments with discrete choices ([Agesti and Hitchcock, 2005](#); [Congdon, 2005](#)) and it is especially suitable in our setup. We can interpret  $\alpha$  as the perception of an individual about the number of people entering competition, while  $\beta$  as the perception about the number of people choosing piece-rate. The mean of the belief distribution of an individual is given by

$$\mu = \frac{\alpha}{\alpha + \beta}$$

Thus, we can infer that  $\mu \in [0, 1]$  represents the individual's prior belief about total competition  $\theta$ , which is equal to the share of people choosing competition,  $k/N$ .

Each agent decides on competition entry by comparing their certain payoff from piece-rate with the expected payoff from tournament, given by  $ca_i f_i(\mu)$ ,  $i \in \{L, H\}$ .<sup>13</sup> Here,  $ca_i$  denotes the total earnings upon winning the tournament, while  $f_i(\mu)$  is the agent's subjective probability of winning the tournament. An agent having a higher belief  $\mu$  expects a larger fraction of participants to choose the tournament. Since high ability agents are more likely to enter the tournament ([Proposition 1](#)), a higher expected entry rate also signals a stronger pool of potential competitors. Facing a stronger opponent pool lowers the subjective probability of winning, and hence  $f_i(\mu)$  is decreasing in  $\mu$ . Conversely, when  $\mu$  is low, the agent expects fewer entrants into the tournament, and hence a weaker pool of competitors, increasing their perceived probability of winning. Therefore, the expected payoff from competing is strictly decreasing in  $\mu$  for both high and low ability agents.

**Property 1.** *Expected payoff from competing decreases with the belief about total competition,  $\mu$ , and this holds true for both high and low ability individuals.*

Further, we can observe that the expected payoff from competing is higher for high ability compared to low ability agents. This is because a high ability agent solves more problems ( $a_H > a_L$ ), and, hence, also has a higher chance of winning the tournament ( $f_H(\cdot) > f_L(\cdot) \forall \mu \in [0, 1]$ ).

**Property 2.** *For every belief  $\mu$ , expected payoff of a high ability individual is higher than a low ability individual.*

We now describe the initial equilibrium of this model in [Proposition 1](#).

**Proposition 1.** *There exists a unique cut-off belief for high ability ( $\mu_H^*$ ) and low ability individuals ( $\mu_L^*$ ), below which they choose to compete, and above which they choose piece-rate. Additionally,  $\mu_H^* > \mu_L^*$ .*

*Proof.* This proof and all subsequent proofs are presented in [Appendix D](#).

This proposition captures the equilibrium of the model, where an individual's choice to compete depends on their belief about the overall competition. Since high ability agents perform better compared to low ability agents, they are more willing to enter the tournament even under higher perceived competition, resulting in higher cut-off beliefs compared to low ability agents.

**Corollary 1.1.** *Assuming high ability and low ability agents are distributed similarly over the beliefs  $\mu \in [0, 1]$ , a larger proportion of high ability individuals will choose to participate in the competition.*

This follows directly from [Proposition 1](#). Since high ability people have a higher cut-off belief compared to low ability people, a higher fraction of high ability agents choose to participate in competition compared to low ability agents, as long as they are similarly distributed over the beliefs  $\mu$ .<sup>14</sup>

The model's mechanism is consistent with our experimental design. In the experiment, an individual's probability of winning the tournament does not mechanically depend on how many others choose to compete in Task 3. Instead, winners are determined by comparing each participant's Task 3 performance with the Task 2 performance of other participants in the session. Consequently,

<sup>13</sup> We assume that, for small payoffs, agents are risk neutral. Hence, they compare the certain payoff from the piece-rate with the expected payoff from entering the competition, to determine their competition choice.

<sup>14</sup> Consistent with this corollary, we empirically find that proportion of high-ability participants (above median level of task performance) choosing competition is significantly higher relative to low-ability participants (see Figure A1 in Appendix A).

observing a higher or lower fraction of agents choosing tournament in Task 3 does not directly affect the payoff from competing. Rather, information about competition is informative about the strength of potential competitors, reflecting the equilibrium selection mechanism emphasized in our model.

### 3.2. Bayesian updating

After choosing between piece-rate and tournament, agents receive information about the total competition, and they interpret this as a signal reflecting the strength of potential competitors. In the *Average* treatment, they learn about the average competition, i.e., out of  $N$  individuals,  $k$  chose competition. Agents use this information to update their prior belief,  $\mu$ , using Bayes' rule as follows,

$$F(\theta|k, N) \propto F(k, N|\theta)F(\theta),$$

where  $F(\theta)$  is the prior belief distribution,  $F(k, N|\theta)$  is the likelihood of observing  $k$  out of  $N$  people choosing competition given competitiveness  $\theta$ , and  $F(\theta|k, N)$  is the posterior updated belief distribution of  $\theta$ . It is well known that conditional on  $\theta$ , the probability of observing  $k$  out of  $N$  people choosing competition follows a Binomial distribution. So,

$$F(k, N|\theta) \propto \theta^k(1 - \theta)^{N-k}.$$

Substituting the expression back in Bayes' rule, we can show that the posterior belief also follows a Beta distribution with

$$F(\theta|k, N) = \text{Beta}(\theta|k + \alpha, N - k + \beta),$$

and the mean of the posterior belief distribution is

$$\tilde{\mu} = \frac{\alpha + k}{\alpha + \beta + N}$$

Using *Beta* distribution as a prior ensures that the updated belief also follows a *Beta* distribution, enabling us to easily calculate the updated belief  $\tilde{\mu}$  using the simple rule derived above.

**Proposition 2.** An individual observing lower competition than their prior belief, i.e.,  $\frac{k}{N} < \mu$ , will update their belief such that  $\frac{k}{N} < \tilde{\mu} < \mu$ . Conversely, the updated belief of an individual observing higher competition than their prior will satisfy  $\frac{k}{N} > \tilde{\mu} > \mu$ .

This proposition shows that the agents will update their beliefs in the direction of new information. If the observed competition is lower than their belief, then they update their belief towards lower competition. On the other hand, if the new information signals higher competition than their original belief, then they update their belief towards higher competition. We now relate this change in belief with the change in competition choice – the primary focus of our paper.

**Proposition 3.** Information and competition choice are related as follows.

- (a) If the observed competition is less than the cut-off belief of low ability agents, i.e.,  $\frac{k}{N} < \mu_L^*$ , then both high and low ability agents increase their competition choice.
- (b) If the observed competition is higher than the cut-off belief of high ability agents, i.e.,  $\frac{k}{N} > \mu_H^*$ , then both high and low ability agents decrease their competition choice.
- (c) If the observed competition is in between, i.e.,  $\mu_L^* < \frac{k}{N} < \mu_H^*$ , then high ability agents increase while low ability agents decrease their competition choice.

In [Proposition 1](#), we proved that high ability agents have a higher cut-off belief ( $\mu_H^*$ ) than low ability agents ( $\mu_L^*$ ). When the observed competition is very low, i.e.,  $\frac{k}{N} < \mu_L^*$ , then both low and high ability agents reduce their belief about the level of competition, and hence, there is an increase in the competition entry among both. Conversely, if the observed competition is too high, i.e.,  $\frac{k}{N} > \mu_H^*$ , then both high and low ability agents update their beliefs towards higher competition, and hence, switch towards piece-rate. Finally, if there is an intermediate level of competition, then high ability agents who initially chose piece-rate reduce their belief about competition and choose to compete while low ability agents who initially chose to compete update their beliefs upward and subsequently leave the competition.

**Corollary 3.1.** Lower the observed competition, higher is the switch towards competition choice, and vice-versa.

As the observed competition is lower, both low and high ability individuals find it more profitable to compete. Hence, those who initially chose piece-rate switch their decision to competition once they receive the information. Additionally, since high ability agents find it more profitable to compete, switching from piece-rate to competition is primarily driven by high ability individuals. Similarly, switch from competition to piece-rate is majorly driven by low ability individuals. We formally prove this result in the corollary below.

**Corollary 3.2.** Switch from piece-rate to competition is primarily driven by high ability individuals who initially chose piece-rate. Conversely, switch from competition to piece-rate is majorly driven by low ability individuals who initially chose competition.

We next compare the behaviour of the individuals under *Average* treatment with those under *Random* treatment.

**Proposition 4.** *Agents receiving a sufficiently strong signal about the choice of  $N > 1$  agents respond more in terms of updating their belief and competition choice compared to those observing the choice of a random individual.*

The proposition shows that the individuals receiving information conveying average competition will update their beliefs and competition choice more compared to those who receive information about the competition choice of a random individual. This is consistent with our prior expectations, as one would give more weight to information coming from a larger group of people than from a random individual.

### 3.3. Discussion

In our analysis so far, we have assumed that the agents have perfect knowledge of their abilities. We now relax this assumption, and agents no longer know their ability with certainty. Let  $\hat{a}$  denote their perceived ability and we can define  $\hat{a}$  as  $\gamma a_H + (1 - \gamma)a_L$ , where  $\gamma \in [0, 1]$  is private information and may vary across agents. Let  $G$  denote the distribution of  $\gamma$  across the agents. Higher the  $\gamma$ , agents believe they are more likely to be of high ability, while lower the  $\gamma$  they believe they are more likely to be of low ability, irrespective of their actual ability. This extension generalizes the baseline two-type model  $(a_H, a_L)$  to a continuum of perceived abilities  $\hat{a}$ , and the baseline model can be considered as a special case in which all low ability agents have  $\gamma = 0$  and all high ability agents have  $\gamma = 1$ .

As long as a positive correlation continues to exist between tournament entry and actual ability, with higher observed competition still signalling a stronger competitive environment, the main predictions of our baseline model regarding social information would continue to hold in this more general environment. A sufficient condition for this is when the conditional distribution of  $\gamma$  among the high ability agents first order stochastically dominates the corresponding distribution among the low ability agents.

**Lemma 1.** *If  $G(\gamma|a = a_H)$  first order stochastically dominates  $G(\gamma|a = a_L)$ , then high ability agents are more likely to choose competition compared to low ability agents.*

Under this condition, agents continue to interpret a higher observed entry rate as signalling a stronger competitive environment, which lowers their perceived chances of winning and therefore reduces tournament entry, while a lower observed entry has the opposite effect. This argument breaks down in environments where  $G(\gamma|a = a_H)$  no longer first order stochastically dominates  $G(\gamma|a = a_L)$ . For instance, if higher tournament entry is believed to be predominantly driven by a disproportionate participation of low ability individuals believing themselves to be of high ability, agents may no longer interpret a high  $k/N$  as indicating tougher competition, in turn weakening or even reversing the baseline response to social information.

### 3.4. Hypotheses

We now list the two main hypotheses arising from the propositions of our model.

Our first hypothesis is about the mechanism through which the information about other subjects' tournament choices influences individual choices. As shown by [Proposition 3](#) in the model, information about a lower (or higher) proportion of others choosing tournament, induces a higher (or lower) likelihood of choosing tournament. We formulate our first research hypothesis as follows:

**Hypothesis 1.** Upon receiving information on the total competition, individuals behave strategically, i.e., lower the observed competition, higher the likelihood of choosing competition, and vice-versa.

Alternatively, there is another channel through which social information can influence competition choice. This is the social learning channel, which predicts that subjects may emulate the choices in conformity with the decision of their competing peers ([Bikhchandani et al., 1998](#); [Fatas et al., 2018](#)). If the information indicates that a higher (or a lower) proportion of other participants have chosen competition, it may induce a behavioral contagion or peer effect, thus, motivating individuals to compete even more (or less) in conformity with the majority behavior. Thus, the two channels a priori predict effects in opposite directions. Which of the two effects persist, is eventually an empirical question.

Next, we turn to our second and main hypothesis. As the model shows, subjects update their beliefs, which in turn affects their competition choice. Thus, following [Proposition 4](#) of our model, we formulate our second research hypothesis:

**Hypothesis 2.** Agents in the *Average* treatment respond to social information relative to the Control treatment, whereas agents in the *Random* treatment show no such response.

We test these hypotheses using the data from the Control and the two information treatments in the next section.

## 4. Results

### 4.1. Descriptive results – willingness to compete

[Table A1](#) reports the summary statistics of outcome variables across the treatments. [Table A2](#) and [Table A3](#) compare the summary statistics of the behavioral measures and demographic variables, respectively. The behavioural measures – contribution in the public good game and risk preference – are by and large balanced across treatments. The demographic variables are balanced across treatments, with no significant differences in the means across treatments for most of the variables. We control for these variables in some of the specifications of the regression analyses.

Starting with the baseline task (Task 3), [Table A1](#) reveals that the proportion choosing tournament is not statistically distinguishable between the control and the treatment groups, i.e., at the baseline task, before the treatment is introduced, there is no statistical difference in competitiveness across the groups. This is reassuring as it suggests that the results obtained in the study are induced by the treatment and not by other participant characteristics. Further, consistent with our model's prediction ([Proposition 1](#), [Corollary 1.1](#)), we find that high-ability participants are more likely to choose competition and are more likely to have higher beliefs about being the winner in their group at the baseline (see [Fig. A1](#) in [Appendix A](#)).

#### 4.2. Information effect

We first test Hypothesis 2, i.e., we examine the effect of social information on the competition choices of the subjects. We estimate the treatment effect of the information provided on competition choice in the treatment round (Task 6), controlling for competition choices in Task 3, using a probit model. We report the marginal effects in [Table 1](#).<sup>15</sup> We closely follow [Niederle & Vesterlund \(2007\)](#)'s estimation strategy to determine our model specifications and control for task performances and predicted ranks in the tasks.<sup>16</sup> In [Table 1](#), the first and the third columns control for task performance, predicted rank (beliefs about one's relative performance in the group), and behavioral measures. The second and fourth columns additionally control for demographic measures. We include session dummies to control for session level unobserved heterogeneity in all the specifications and report robust standard errors.<sup>17</sup> We find that, the *Average* treatment, where we provide information about the proportion of participants in the session choosing tournament, increases the likelihood of subjects choosing tournament in Task 6 by 8 to 9 percentage points (col (1)-(2) in [Table 1](#)), as compared to the control sessions.

**Result 1.** Social information about the percentage of other participants choosing Rule-100 (tournament) increases the likelihood of tournament entry. This is not driven by the salience of the term "Rule-100".

Can this result be explained by a Salience Effect? As discussed earlier, the treatment effect we observe may arise because of participants' response to the proportion of participants choosing 'Rule-100' or it may arise simply because of the salience of the term 'Rule-100' presented in the information. The information presented in the *Random* treatment allows us to test if the treatment effect is driven by salience. Col (3)-(4) of [Table 1](#) presents the regression results from a probit model, and the dummy for *Random* treatment is statistically insignificant for all the specifications. Thus, providing information about the choice made by a randomly selected participant does not influence individuals' subsequent decision to compete, relative to the control. This is also clear from [Table 2](#) when competition choice in Task 6 is regressed on dummies created for Rule-25 (piece-rate) and Rule-100 (tournament). Neither coefficient is statistically significant. Taken together, this suggests that the effect observed in the *Average* treatment is not driven by salience, but rather by social information.

Further, this result is consistent with [Proposition 4](#) of our model, and supports Hypothesis 2, which predicts that agents in the *Average* treatment will be more responsive to social information than those in the Control, whereas agents in the *Random* treatment do not exhibit a differential response relative to the Control.

Having established that social information affects the likelihood of subjects choosing to compete, we next investigate whether this effect is driven by strategic considerations or by conformism. Information about competitiveness can have two opposite effects. A participant may feel encouraged by others' competitiveness, and consequently, she may be more inclined to compete. A participant may also behave strategically, in the sense that she may be less likely to compete if others compete more, since that may reduce her perceived chance of winning. [Proposition 3](#), specifically [Corollary 3.1](#) of our model argues that agents behave strategically with higher overall competition leading to less people entering the tournament. Using our experiment, we can test the model's predictions and determine which of the two opposing effects is supported by the data, and therefore, test Hypothesis 1. Recall that in the *Average* treatment, the participants are shown the proportion of subjects who chose Rule-100 (tournament) in Task 3 of that session. This proportion varied between 27 % and 55 % across the sessions.<sup>18</sup> We use this variation to test whether the overall treatment effect discussed in Result 1 arises from sessions that observe low average competition or those that see high average competition. To do so, we categorize the continuous measure of average competition into two groups using a threshold of 40 %. The choice for 40 % cut-off is based on the overall average of 39.75 % of participants choosing the tournament in Task 3. This categorization allows us to examine how an individual's competition choice responds to the observed choices of others. Note that for the estimates of "Average below 40" and "Average above 40" to be unbiased, the variation in these should be exogenous to the outcome variables. Indeed, in our case, these two variables are exogenous to a participant, even though the average competition levels that generate these two variables are determined within a session. In other words, the average competition level in a session is unlikely to be influenced by any single participant in a session averaging 44 individuals. For the corresponding analyses involving the *Random* treatment, where the subjects

<sup>15</sup> We also estimate the treatment effects using a linear probability model (LPM), and find the results are analogous to the average marginal effects from probit regression.

<sup>16</sup> As the subjects participate in four rounds of the real effort task, we include task performance of all the rounds in our regressions to control for learning or experience with the task. The full table with all the controls is presented in [Table A4](#).

<sup>17</sup> The unit of randomization here is an individual. Thus, we report robust standard errors. The results are robust to alternate specifications such as standard errors clustered at the session level.

<sup>18</sup> The proportion as seen by participants in the *Average* treatment as well as the information seen by participants in the *Random* treatment, by each session is presented in [Table A5](#).

**Table 1**  
Treatment effect on tournament entry in task 6.

VARIABLES	Average Treatment		Random Treatment	
	Task 6 Competition Choice			
	(1)	(2)	(3)	(4)
Average	0.083* (0.049)	0.096** (0.046)		
Random			0.067 (0.052)	0.056 (0.050)
Task 3 Pred Rank	-0.114*** (0.036)	-0.140*** (0.037)	-0.077** (0.039)	-0.073** (0.037)
Task 3 Choice	0.347*** (0.035)	0.350*** (0.035)	0.344*** (0.043)	0.354*** (0.041)
Observations	202	202	205	205
Demographic controls	No	Yes	No	Yes

Notes: The table reports marginal effects from probit regressions. The dependent variable is an indicator for choosing Rule-100 (tournament) in Task 6 (yes: 1, no: 0). All specifications include session dummies to control for unobservable session heterogeneity. Behavioral measures include measures for risk preference, cooperation, and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1) and (3) controls for task performances in tasks 1,2,3, and behavioral measures. Col (2) and (4) add controls for demographic measures. Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$

\*\*  $p < 0.05$

\*  $p < 0.1$ .

**Table 2**  
Effect of information on tournament entry in task 6.

VARIABLES	Average Treatment		Random Treatment	
	Task 6 Competition Choice			
	(1)	(2)	(3)	(4)
Average below 40	0.157** (0.074)	0.149** (0.074)		
Average above 40	0.027 (0.064)	0.055 (0.060)		
Rule-25			0.063 (0.079)	0.031 (0.076)
Rule-100			0.071 (0.070)	0.076 (0.069)
Task 3 Choice	0.332*** (0.036)	0.338*** (0.036)	0.344*** (0.043)	0.357*** (0.041)
Observations	202	202	205	205
Demographic controls	No	Yes	No	Yes

Notes: The table reports the marginal effects from probit regressions. The dependent variable is an indicator for choosing Rule-100 (tournament) in Task 6 (yes: 1, no: 0). The Average below 40 (or above 40) indicates whether the subjects in the *Average* treatment see the average competition choice in Task 3 as below 40 percent (or above 40 percent). The Rule-100 (or Rule-25) indicates whether the subjects in the *Random* treatment see the choice of the randomly chosen participant in Task 3 as Tournament (or Piece-rate). All specifications include session dummies to control for unobservable session heterogeneity. Behavioral measures include measures for risk preference, cooperation, and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1) and (3) controls for task performances in tasks 1,2,3 and behavioral measures. Col (2) and (4) add controls for demographic measures. Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

observe the decision of a randomly chosen player (Rule-25 (piece-rate) or Rule-100 (tournament)), we examine how their competition choice depends on the rule they see.<sup>19</sup>

The regression results are presented in Table 2 (the column specifications are the same as in Table 1).<sup>20</sup> Within the *Average* treatment, as col (1) reports, controlling for task performances, belief, and behavioral measures, we find that, subjects who learn that <40 % of participants chose competition, are 16 percentage points more likely to choose tournament relative to the control treatment ( $p$ -value = 0.035). In the more stringent specification reported in col (2), that number is 15 percentage points ( $p$ -value = 0.073).

<sup>19</sup> In the control group, the proportion of subjects choosing Rule-100 in Task 6, conditional on choosing Rule-25 or Rule-100 in Task 3, is 0.09 and 0.77, respectively (see Table A1 for details). Using these control proportions (0.09 and 0.77) and sample sizes of 100 in the control group and 47 in the treatment group, we obtain minimum detectable effects (MDEs) of 0.13 and 0.16 for 80 percent power at the 10 percent and 5 percent significance levels, respectively. These MDEs align closely with our observed effect sizes.

<sup>20</sup> Full table with all the controls is presented in Table A6.

However, we do not find any significant effect when subjects learn that the proportion of subjects choosing the tournament is higher than 40 percent.<sup>21</sup> This suggests that the treatment effect for the *Average* treatment is driven mainly by the subjects observing a lower percentage of competition choice. Thus, we find that the effect of social information on competition choice runs contrary to the notion of conformity or peer effect. Instead, our results are consistent with [Proposition 3](#) and Hypothesis 1 and can be stated as follows:

**Result 2** The social information conveying lower competitiveness of other participants significantly increases the likelihood of choosing competition.

We next discuss two likely concerns regarding our results. First, with the *Average* treatment conveying information about the mean tournament entry in the same session, can there be potential endogeneity concerns? As discussed earlier, the average tournament entry choice is endogenous to a session but remains exogenous to an individual participant. Second, can the results be explained by a higher propensity for tournament entry in sessions that had low proportion of tournament entry at the baseline? We address this concern in two ways: (1) by controlling for each individual's competition choice in the baseline round in our regressions, and (2) by employing session fixed effects, which allow us to estimate the tournament entry in the average treatment relative to control within the same session.

#### 4.3. Mechanism

Next, we explore whether participants' decisions to compete are influenced by treatment-induced beliefs regarding their chances of winning the tournament. Our theoretical model suggests that information about the proportion competing is likely to shape subjects' beliefs about winning. To test this, we use data on participants' beliefs about being the winner in their group, i.e., winning the tournament, expressed in percentage probability, and compare beliefs across treatments. We collected the beliefs data for each of the choice rounds. Between Task 3 and Task 6, we expect that the beliefs about being the winner could increase due to a learning effect.<sup>22</sup> Thus, we analyse the shifts in beliefs across the treatments, by comparing the change in the reported chance of winning by information within treatments as shown in [Fig. 1](#).

Notes: [Fig. 1](#) presents the change in beliefs about winning (being the top performer in the group) in Task 6 compared to belief in Task 3 by information within treatments. The difference between Control and 'Average below 40' is 5.98 percentage points (pp) (*t*-test, *p*-value=0.087). The Average below 40 (or above 40) indicates whether the subjects in the *Average* treatment see the average competition choice in Task 3 as below 40 percent (or above 40 percent). The Rule-100 (or Rule-25) indicates whether the subjects in the *Random* treatment see the choice of the randomly chosen participant in Task 3 as Tournament (or Piece-rate). The whiskers indicate the 95 % confidence interval.

We find that the information stating that the average tournament entry was below 40 % (indicated by 'Average below 40') significantly increases the beliefs about winning by 5.98 percentage points (*t*-test, *p*-value = 0.087).<sup>23</sup> The other information categories do not significantly affect the beliefs about winning the tournament. These results indicate that the information provided in the *Average* treatment, particularly the information conveying lower tournament entry, increases the subjects' beliefs about winning the tournament, and hence, induces them to choose competition. The positive effect of 'Average below 40' on belief about winning in Task 6 is robust to including performance, behavioral, and demographic measures in regression analysis, as shown in [Table A8](#) in [Appendix A](#). Thus, consistent with the predictions of [Proposition 2](#) in our model, we find evidence for beliefs moving in the direction of information under *Average* treatment. Consistent with our expectations for [Proposition 4](#), in the *Random* treatment case we do not find any significant effects.

Even though information conveying low competition ('Average below 40') shifts beliefs consistent with the direction predicted by the model, information indicating high competition ('Average above 40') does not have any significant effect on the beliefs. A plausible explanation for this could be the nature of our subject pool. As discussed in [Section 2.3](#), participants were recruited from the flagship two-year MBA program and admitted through a highly competitive selection process. It is therefore quite likely that subjects enter the experiment with relatively high prior expectations about how competitive their peers are. If the subjects expect a (relatively) highly competitive environment, then information indicating high competition is largely confirmatory and does not lead to large revisions in beliefs. In contrast, information indicating low competition is more surprising, and therefore, produces a stronger update of beliefs in the direction consistent with the model mechanism. This could explain why beliefs respond strongly to low-competition information but only weakly to high-competition information.

Importantly, our design provides information about others' participation decisions but does not reveal realized payoffs. Experimental evidence demonstrates that rational, incentive-compatible outcomes regularly emerge in private information environments, even when agents cannot observe others' payoffs, because individuals rationally update on available institutional signals ([Smith, 1991](#)). Consistent with this, our design isolates belief updating based solely on participation rates as the relevant institutional signal. Canonical observational learning models confirm that individuals can rationally update beliefs from others' actions even without

<sup>21</sup> Note that the cutoff of 40% is based on the overall proportion of tournament entry in Task 3 across all sessions. The proportion of subjects who choose Rule-100 (tournament) in Task 3 varied between 27 and 55 percent across the sessions. Thus, we test these results with possible alternative cutoffs such as 37, 41, and 42. We find that the results are robust to different cutoffs and these are presented in [Table A7](#).

<sup>22</sup> We do see this pattern in the data. One reason is the subjects compete against the performance of other subjects in Task 2, and performance of the subjects improves with repetition of tasks.

<sup>23</sup> The belief updating results are robust to alternative cut-offs such as 37, 41, and 42 to categorize the information in the *Average* treatment. While 'Average below 'X' increases beliefs about winning, 'Average above 'X' lowers the beliefs about winning. Results are available on request.

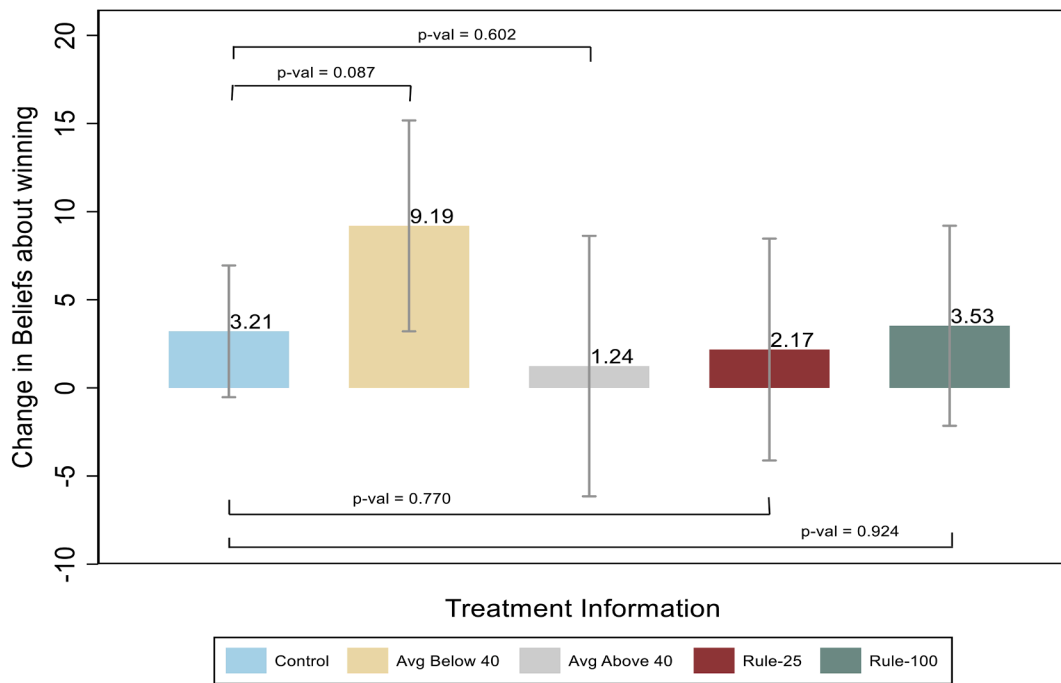


Fig. 1. Change in beliefs about winning by treatment.

observing payoffs (Banerjee, 1992; Bikhchandani et al., 1992). Thus, in our context, belief shifts arise from the informational content of competition rates rather than payoff. Consistent with this, we do not find evidence of social conformity: participants do not conform to observed participation rates but instead respond strategically, updating their beliefs about winning probabilities.

## 5. Additional results

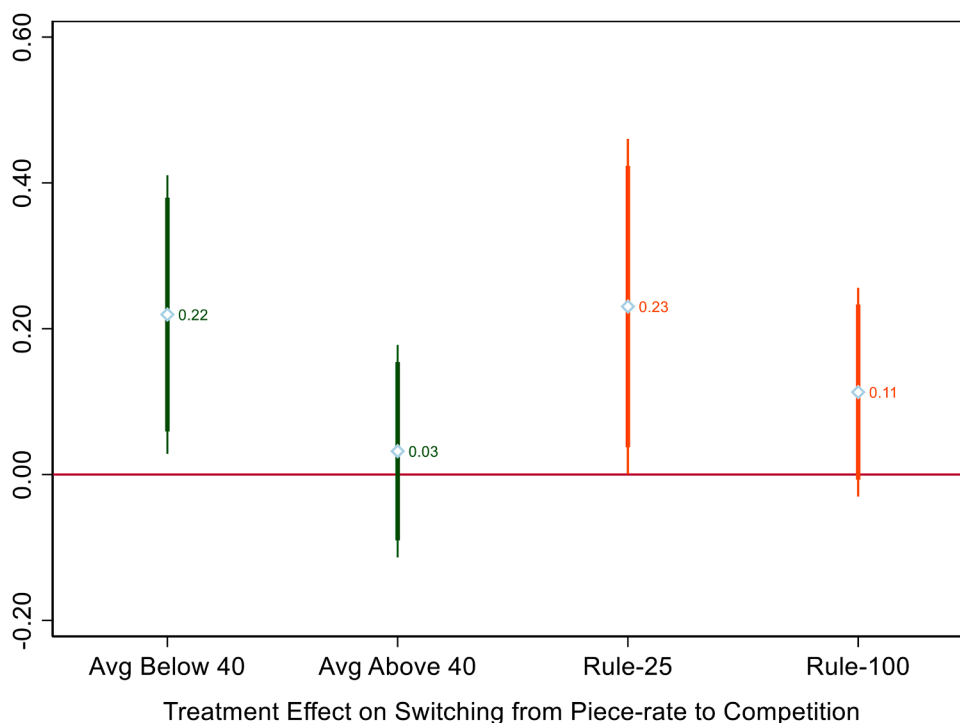
### 5.1. Who are the subjects switching to competition?

So far, we have found that the information about the competition choices of other participants impacts the likelihood of subjects choosing competition. We have done this by comparing the competition choice in Task 6, while controlling for the subjects' choice in the baseline round. An alternative way to analyse this would be to compare the within-subject change in competition choice. We thus analyse how the information provided in the treatment affects the switching of choice from piece-rate to competition and from competition to piece-rate. We hereafter refer to these choice switches as P2C and C2P, respectively. For subjects who initially make a piece-rate choice in Task 3, P2C takes the value of 1 when they switch their choice to tournament in Task 6 and takes the value of 0 when they retain their original choice of piece-rate. Similarly, for subjects who initially choose tournament in Task 3, C2P takes the value of 1 when they switch their choice to piece-rate in Task 6 and takes the value of 0 when they retain their original choice of tournament. It is important to note that, in this analysis, we have a restricted sample of subjects who initially chose piece-rate for P2C (tournament for C2P) and are likely to have a lower (higher) willingness to compete.

Using P2C as the dependent variable, we estimate the effect of information on competition entry, and plot this in Fig. 2.<sup>24</sup> We find that information conveying low average competitiveness (i.e., 'Average below 40') increases the likelihood of switching to competition by 22 percentage points (p-value = 0.024). So far in our analysis, we have observed that the Random treatment does not have a significant effect on competition entry in the full sample. However, within this restricted subsample of participants who initially chose piece-rate, we find Rule-25 significantly increases the likelihood of switching to competition by 23 percentage points (p-value = 0.049).<sup>25</sup> Although these treatment effects are specific to only subjects who initially chose piece-rate (having lower baseline willingness to compete), the results are consistent with our model predictions where we expect that, lower the observed competition, higher will be the switch to competition, and vice-versa (Proposition 3, Corollary 3.1). The significant treatment effect for 'Average

<sup>24</sup> The estimates are from regression analysis that uses the same specification presented in Table 2. The detailed regression results are presented in Table A9 in Appendix A.

<sup>25</sup> Recall, we do not find a significant response to Rule-25 in the full sample (Table 2), indicating that this information does not uniformly affect all participants but primarily influences those who are less likely to choose competition in the first place.



**Fig. 2.** Treatment effect of information on switching from piece-rate to competition.

Notes: Fig. 2 reports the estimated marginal effects at the mean from probit regressions. The dependent variable is an indicator for choosing Rule-100 (tournament) in Task 6 (yes: 1, no: 0) conditional on making an initial choice of piece-rate in Task 3. The Average below 40 (or above 40) indicates whether the subjects in the *Average* treatment see the average competition choice in Task 3 as below 40 percent (or above 40 percent). The Rule-100 (or Rule-25) indicates whether the subjects in the *Random* treatment see the choice of the randomly chosen participant in Task 3 as Tournament (or Piece-rate). The thick (thin) line across an estimate represents the 90 % (95 %) confidence interval.

below 40' in *Average* treatment and for 'Rule-25' in the *Random* treatment further substantiate our earlier result that the social information affects the competition choice through the strategic channel.

### 5.2. Choice switches by ability

An important question is whether those who switch to competition are high-ability individuals who initially chose the piece-rate scheme due to low beliefs about winning but later revise their beliefs upward in response to new information. To test this, we compare subjects' ability across their tournament choices in Task 3 and Task 6, respectively. As a measure of ability relevant to our context, we combine performance in Task 1, Task 2, and Task 3 (tasks before Task 6) using principal component analysis (PCA) and take the first principal component as our measure of ability. Mean ability by tournament choice is presented in Fig. 3, with positive ability scores representing high ability, and the negative scores signifying low ability.

We find that, those who initially choose piece-rate in Task 3 and choose piece-rate in Task 6 (P2P) are predominantly of low ability (PCA of scores =  $-0.33$ ,  $p$ -value  $< 0.01$ ), while those who consistently choose competition in both the rounds (C2C) are, on average, high ability (PCA of scores =  $0.57$ ,  $p$ -value  $< 0.01$ ). These patterns provide support to the arguments extended by our model in Proposition 1, Corollary 1.1. The other point estimates, though not significantly different from zero, indicate that those who switch from piece-rate to competition (P2C) are on average high ability individuals, while those who switch from competition to piece-rate (C2P) are largely of low ability. Overall, these results are again consistent with our model predictions as stated in Proposition 3, Corollary 3.2.

Note that in our setting, the data suggests that the P2C switch is not sub-optimal, in the sense that those who switch do not receive lower earnings. In Table A10, we report the results from a regression where the payoffs of the subjects are regressed on the treatment dummies, the indicator for switching to competition, and the interactions, besides other covariates. The interaction terms are not significant for either treatment.

### 5.3. Treatment heterogeneity by gender

In this section, we examine whether the information has differential effects on females compared to males. First, in our sample, we replicate the gender gap in competition choice in Task 3, a pattern that has been widely documented in the literature. The gender difference in the likelihood of choosing competition in Task 3 is 21 percentage points (Fisher's exact test,  $p$ -value  $< 0.01$ ), and 14

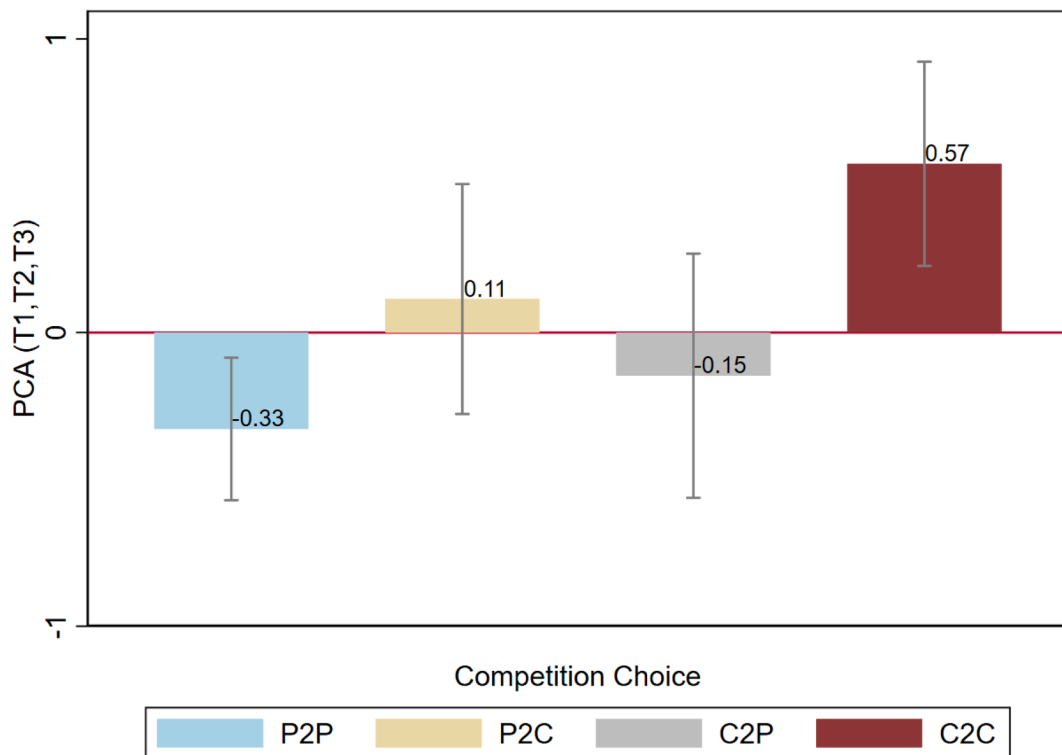


Fig. 3. Comparison of ability by choice switchers.

Notes: Fig. 3 plots the mean measure of ability, which is the first component of PCA of performance in Tasks 1, 2, and 3. The reported mean values are computed using the pooled sample across all treatment groups. P2C refers to participants who initially choose piece-rate in the baseline task but then switch to competition in the treatment round. C2P refers to participants who initially choose tournament in the baseline task but then switch to piece-rate in the treatment round. P2P and C2C refers to participants who always chose piece-rate or tournament respectively in both rounds.

Table 3

Heterogeneous effect of information by gender – results from probit regression with gender and treatment information interactions.

VARIABLES	Average Treatment		VARIABLES	Random Treatment	
	(1)	(2)		(3)	(4)
	Task 6 Competition Choice				
Average below 40	0.348 (0.362)	0.390 (0.406)	Rule-25	0.282 (0.383)	0.177 (0.402)
Average above 40	0.152 (0.391)	0.195 (0.372)	Rule-100	0.150 (0.310)	0.175 (0.314)
Female	0.017 (0.347)	-0.088 (0.372)	Female	-0.120 (0.333)	-0.151 (0.347)
Female # Average below 40	1.297** (0.621)	1.459** (0.672)	Female # Rule-25	0.050 (0.659)	0.004 (0.666)
Female # Average above 40	0.039 (0.593)	0.315 (0.636)	Female # Rule-100	0.695 (0.604)	0.789 (0.640)
Observations	202	202	Observations	205	205
Demographic controls	No	Yes	Demographic controls	No	Yes

Notes: The table reports the estimated effects from probit regressions. The dependent variable is an indicator for choosing Rule-100 (tournament) in Task 6 (yes: 1, no: 0). The Average below 40 (or above 40) indicates whether the subjects in the *Average* treatment see the average competition choice in Task 3 as below 40 percent (or above 40 percent). The Rule-100 (or Rule-25) indicates whether the subjects in the *Random* treatment see the choice of the randomly chosen participant in Task 3 as Tournament (or Piece-rate). All specifications include session dummies to control for unobservable session heterogeneity. Behavioral measures include measures for risk preference, cooperation, and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1) and (3) controls for task performances in tasks 1,2,3 and behavioral measures. Col (2) and (4) add controls for demographic measures. Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$ .

\*\*  $p < 0.05$

\*  $p < 0.1$ .

percentage points in Task 6 (Fisher's exact test,  $p$ -value=0.033). We also find that male and female subjects are significantly different in their mean task performance distribution (Kolmogorov-Smirnov test,  $p$ -value<0.01, refer to Fig. A2 in Appendix A). The gender gaps in competition choice persist even after controlling for the differences in performance, but not when we control for risk preferences and predicted ranks (refer to Table A11 in Appendix A). This is consistent with recent studies which find that gender differences in entry into competition is entirely explained by gender differences in risk attitude and self-confidence (Gillen et al., 2019; van Veldhuizen, 2022).

We then test if social information has differential effects for female subjects. We do not find any significant differences in treatment effects across gender for the overall treatment condition (refer to Table A12 in Appendix A). We further analyse the heterogeneous effects of the information on competitiveness by including interactions of the female dummy with the dummies for 'Average below 40' and 'Average above 40' categories within each treatment. The results are reported in Table 3.

In the *Average* treatment, with the interactions in place, we find that the treatment effects for 'Average below 40' as well as 'Average above 40' are not significant across specifications. However, we find that the interaction term for females and 'Average below 40' is positive and significant at 5 % level. This suggests that females choose to compete more when they realize that others are not competing too much.

## 6. Discussion and conclusion

In this paper, we have investigated how social information affects competition choice. We inform individuals about the competition choice of the participant pool and examine how this information affects their willingness to compete. We provide this information in two forms. In the *Average* treatment, we inform the subjects about the proportion of participants who chose to compete in the previous round. This information significantly increases the likelihood of choosing to compete, controlling for the baseline willingness to compete. We find that this effect is driven mainly by the subjects who learn that the average competitiveness is low. In the *Random* treatment, where the subjects are informed about the competition choice of a randomly chosen participant, we do not observe any significant treatment effects.

Among those who do not choose competition in the baseline round, we find that the information conveying a low level of competition induces the subjects to switch to competition in the treatment choice round. We observe that the subjects switching to competition are similar in task ability to the subjects choosing competition initially. On average, a switch from an initial piece-rate (safer) choice to competition (riskier), does not negatively affect the payoffs of subjects.

Our paper offers novel policy insights by demonstrating the powerful role that social information about others' competition choices can play in encouraging participation. In organizational settings characterized by heterogeneity in employee capabilities and risk preferences, people may avoid competition based on inaccurate beliefs about the competitive landscape. Our results indicate that social information about the general level of competitiveness can help those at the margin to compete, particularly in one-shot strategic environments.

This has several practical implications for the structure of selection and promotion processes. First, transparency in promotion processes can have strategic consequences—when organizations make application pools visible, revealing low application rates may attract additional candidates who update their beliefs about the competitive landscape, potentially altering the composition and quality of the applicant pool. Second, these findings are particularly relevant given evidence that employees, especially women, often volunteer for low-promotability tasks rather than competing for high-promotability opportunities (Babcock et al., 2017; Banerjee and Mustafi, 2025). Providing information about peer participation in competitive opportunities could help individuals make more strategic career decisions by signalling when competition is less intense than anticipated. This can have a disproportionate effect on social groups who are underrepresented in competitive environments. Third, the results have implications for platforms and HR systems (such as LinkedIn or internal applicant tracking systems) that display real-time application statistics, as our evidence indicates that such features actively shape competitive behavior through strategic learning mechanisms. Notably, such information can serve either as a behavioral nudge or as an instrument for rational Bayesian belief updating. Our investigation provides stronger support for the latter mechanism. The general equilibrium effects of such information provision represent an important avenue for future research.

## Declaration of competing interest

The authors have no conflict of interest to declare or disclose. Also, there are no financial disclosures to declare. Authors: Ritwik Banerjee, Lata Gangadharan, Anand Kumar, Srinivasan Murali

Appendix A

Fig. A2, Table A4, Table A5, Table A6, Table A7, Table A8, Table A9, Table A10, Table A11, Table A12

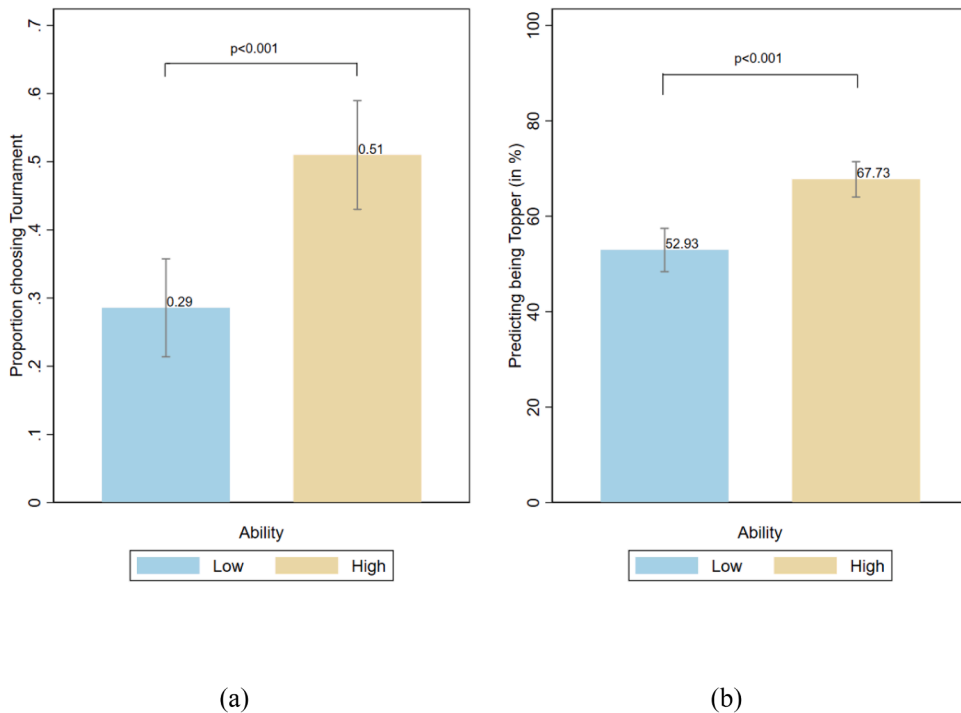
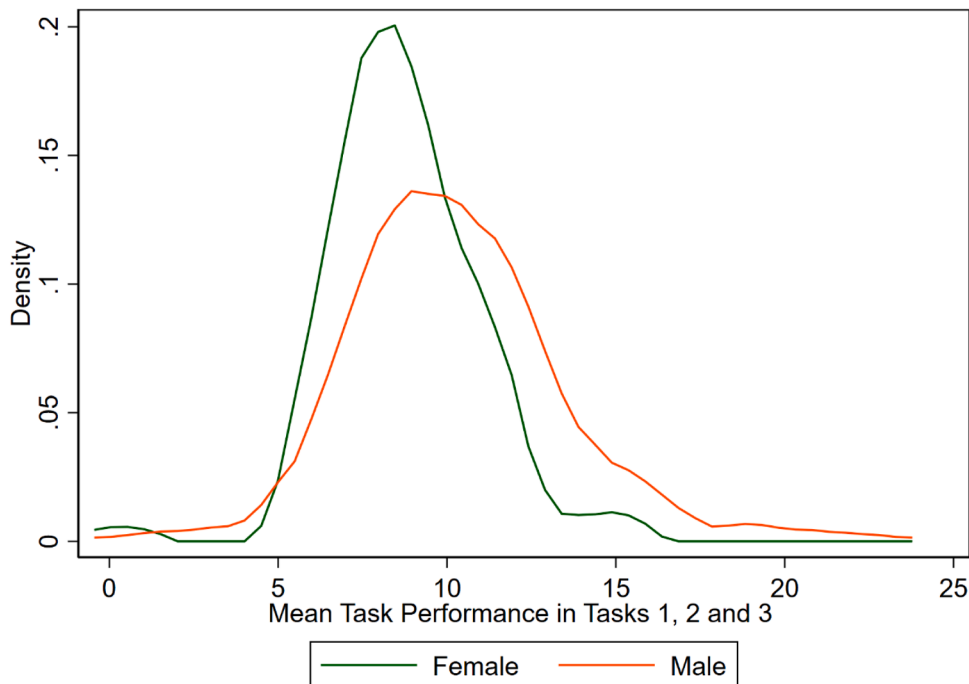


Fig. A1. Competition choice and beliefs by ability.

Notes: Fig. A1(a) presents the proportion of subjects who choose tournament (Rule-100) in Task 3. The measure of ability is the first component of the PCA of performance in Tasks 1, 2, and 3. For the analysis participants are categorized into below and above the median measure of ability, Low and High, respectively. The difference between Low ability and High ability participants is 22 percentage points (pp) (Fisher's exact test,  $p$ -value < 0.01). Fig. A1(b) presents the beliefs about being the winner in the group in Task 3, reported in percentage probability. The difference between Low and High ability participants is about 14 percentage points (pp) ( $t$ -test,  $p$ -value < 0.01). The whiskers indicate the 95 % confidence interval.



**Fig. A2.** Comparison of mean task performance between male and female.

Notes: The figure plots the distribution of mean performance over Tasks 1, 2, and 3 between male and female participants. The male and female participants have different distribution of mean task scores. The Kolmogorov–Smirnov test for equality of distribution functions returns a p-value <0.01.

**Table A1**  
Summary statistics – task related outcomes.

Variable	Definition	(1) Control Mean	(2) Average Mean	(3) Random Mean	(4) Difference (1)-(2)	(5) p- value (1)- (2)	(6) Difference (1)-(3)	(7) p- value (1)- (3)
Task 1	Number of right responses in Piece-Rate Round (Task 1)	9.330	9.039	8.657	0.291	0.546	0.673	0.187
Task 2	Number of right responses in Tournament Round (Task 2)	10.990	10.765	10.486	0.225	0.640	0.504	0.281
Rank in Task 2	Rank in group in Tournament Round (Task 2)	2.380	2.480	2.610	-0.100	0.578	-0.230	0.307
Competition Task 3	Proportion choosing Tournament in Choice Round (Task 3)	0.440	0.343	0.410	0.097	0.194	0.030	0.674
Task 3	Number of right responses in Choice Round (Task 3)	9.990	9.745	9.829	0.245	0.620	0.161	0.755
Rank in Task 3	Rank in group in Choice Round (Task 3)	2.370	2.510	2.562	-0.140	0.765	-0.192	0.224
Competition Task 6	Proportion choosing Tournament in 2nd Choice Round (Task 6)	0.390	0.382	0.410	0.008	0.912	-0.020	0.777
Task 6	Number of right responses in 2nd Choice Round (Task 6)	12.500	11.951	11.924	0.549	0.327	0.576	0.302
Rank in Task 6	Rank in group in 2nd Choice Round (Task 6)	2.330	2.490	2.610	-0.160	0.129	-0.280*	0.027
P2C	Proportion choosing Tournament in 2nd Choice Round (Task 6) conditional on choosing piece rate in Task 3	0.089	0.194	0.210	0.105	0.103	0.121*	0.070
C2C	Proportion choosing Tournament in 2nd Choice Round (Task 6) conditional on choosing Tournament rate in Task 3	0.773	0.743	0.698	-0.030	0.761	-0.075	0.664
Sample Size		100	102	105				

Notes: The table reports summary statistics of the task related outcomes analysed in the paper. For variables that denote number or rank, we report p-values from two sample t-test. For variables that denote proportions, we report p-values from Fisher’s Exact test. \*  $p < 0.10$ .

\*\*  $p < 0.05$ .

\*\*\*  $p < 0.01$ .

**Table A2**  
Summary statistics – behavioral measures.

Variable	Definition	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Control Mean	Average Mean	Random Mean	Difference (1)-(2)	p-value	Difference (1)-(3)	p-value
Contribution to Public Good Game (PGC)	Proportion of endowment contributed to the public goods game from Task 4	0.550	0.598	0.590	-0.048	0.584	-0.040	0.657
Risk Preference	Risk aversion coefficient obtained from Task 5 (Holt and Laury, 2002)	0.180	0.188	0.217	-0.008	0.919	-0.037	0.614
Optimism	Measure based on Life Orientation Test (0-4) (Scheier et al., 1994)	2.532	2.382	2.317	0.149*	0.089	0.214**	0.0163
Sample Size		100	102	105				

Notes: The table reports summary statistics of the behavioral variables used in the paper. The complete questionnaire can be found in Appendix C. For continuous variables, we report p-values from two sample *t*-test. For variables that denote proportions, we report p-values from Fisher’s Exact test. \* *p* < 0.10.

\*\* *p* < 0.05  
\*\*\* *p* < 0.01.

**Table A3**  
Summary statistics – demographic measures.

Variable	Definition	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Control Mean	Average Mean	Random Mean	Difference (1)-(2)	p-value	Difference (1)-(3)	p-value
Age	Age in Years	24.530	24.620	24.486	-0.090	0.713	0.044	0.845
Female	Proportion of females	0.220	0.245	0.305	-0.025	0.740	-0.085	0.205
Caste: General	Proportion of General Castes	0.520	0.549	0.552	-0.029	0.778	-0.032	0.676
Caste: OBC	Proportion of Other Backward Castes	0.280	0.265	0.248	0.015	0.875	0.032	0.636
Caste: SC/ST	Proportion of Scheduled Castes or Scheduled Tribes	0.180	0.176	0.190	0.004	1.000	-0.010	0.860
Religion: Hindu	Proportion of Hindus	0.880	0.833	0.914	0.047	0.423	-0.034	0.493
Class 10	School Marks– Class X	93.238	93.746	93.615	-0.508	0.274	-0.377	0.459
Class 12	School Marks– Class XII	90.498	90.679	91.253	-0.182	0.842	-0.755	0.381
Work Experience	Proportion of previously worked individuals	0.850	0.873	0.867	-0.023	0.688	-0.017	0.842

Notes: The table reports summary statistics of the demographic and behavioral variables used in the paper. The categories under Religion are Buddhists, Christians, Hindus, and Muslims. In this table, only the proportion of Hindu is reported. The complete questionnaire can be found in Appendix C. For continuous variables, we report p-values from two sample *t*-test. For variables that denote proportions, we report p-values from Fisher’s Exact test. \* *p* < 0.10.

\*\* *p* < 0.05.  
\*\*\* *p* < 0.01.

**Table A4**  
Treatment effect on tournament entry in task 6 (full table).

VARIABLES	Average Treatment		Random Treatment	
	Task 6 Competition Choice			
	(1)	(2)	(3)	(4)
Average	0.083* (0.049)	0.096** (0.046)		
Random			0.067 (0.052)	0.056 (0.050)
Task 3 Choice	0.347*** (0.035)	0.350*** (0.035)	0.344*** (0.043)	0.354*** (0.041)
Task 3 Pred Rank	-0.114*** (0.036)	-0.140*** (0.037)	-0.077** (0.039)	-0.073** (0.037)
Task 1 Performance	0.008 (0.010)	0.009 (0.010)	0.012 (0.010)	0.009 (0.010)
Task 2 Performance	-0.008 (0.011)	-0.009 (0.011)	0.006 (0.011)	0.004 (0.011)
Task 3 Performance	0.004 (0.013)	0.002 (0.012)	0.000 (0.012)	0.000 (0.012)
Public Good Contribution	0.000 (0.051)	-0.000 (0.050)	-0.033 (0.054)	-0.054 (0.054)
CRRA	-0.192*** (0.047)	-0.219*** (0.050)	-0.115** (0.057)	-0.125** (0.063)
Optimism	0.082** (0.038)	0.081** (0.040)	0.049 (0.042)	0.058 (0.044)
Observations	202	202	205	205
Demographic controls	No	Yes	No	Yes

Notes: The table reports the marginal effects from probit regressions. The dependent variable is an indicator for choosing Rule-100 (tournament) in Task 6 (yes: 1, no: 0). All specifications include session dummies to control for unobservable session heterogeneity. Behavioral measures include measures for risk preference, cooperation, and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1) and (3) controls for task performances in tasks 1,2,3, and behavioral measures. Col (2) and (4) add controls for demographic measures. Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$ .

\*\*  $p < 0.05$ .

\*  $p < 0.1$ .

**Table A5**  
Information in task 6 by treatment groups and by session.

Session	Average (1)	Random (2)	Participants (3)
1	41.67	Rule-25	35
2	40.00	Rule-100	60
3	38.46	Rule-25	51
4	43.75	Rule-100	30
5	27.08	Rule-100	48
6	36.36	Rule-25	43
7	55.00	Rule-25	40

Notes: The table reports the information provided to participants before Task 6 in each session. Column (1) reports the information about the percentage of participants who chose Rule-100 (tournament) in Task-3. Column (2) reports the choice of the participants randomly chosen from Task-3. Column (3) reports the total number of participants in the session.

**Table A6**  
Effect of information on tournament entry in task 6 (full table).

VARIABLES	Average Treatment		Random Treatment	
	(1)	(2)	(3)	(4)
Average below 40	0.157** (0.074)	0.149** (0.074)		
Average above 40	0.027 (0.064)	0.055 (0.060)		
Rule 25			0.063 (0.079)	0.031 (0.076)
Rule 100			0.071 (0.070)	0.076 (0.069)
Task 3 Choice	0.332*** (0.036)	0.338*** (0.036)	0.344*** (0.043)	0.357*** (0.041)
Task 3 Pred Rank	-0.118*** (0.035)	-0.140*** (0.036)	-0.077** (0.039)	-0.071* (0.036)
Task 1 Performance	0.009 (0.011)	0.010 (0.010)	0.012 (0.010)	0.010 (0.011)
Task 2 Performance	-0.008 (0.010)	-0.009 (0.011)	0.006 (0.011)	0.004 (0.011)
Task 3 Performance	0.004 (0.013)	0.003 (0.012)	-0.000 (0.012)	-0.000 (0.012)
Public Good Contribution	-0.003 (0.050)	-0.002 (0.050)	-0.033 (0.054)	-0.052 (0.054)
CRRA	-0.199*** (0.048)	-0.222*** (0.050)	-0.114** (0.057)	-0.125** (0.063)
Optimism	0.081** (0.038)	0.080** (0.039)	0.049 (0.042)	0.058 (0.044)
Observations	202	202	205	205
Demographic controls	No	Yes	No	Yes

Notes: The table reports the marginal effects from probit regressions. The dependent variable is an indicator for choosing Rule-100 (tournament) in Task 6 (yes: 1, no: 0). The Average below 40 (or above 40) indicates whether the subjects in the *Average* treatment see the average competition choice in Task 3 as below 40 percent (or above 40 percent). The Rule-100 (or Rule-25) indicates whether the subjects in the *Random* treatment see the choice of the randomly chosen participant in Task 3 as Rule-100 (or Rule-25). All specifications include session dummies to control for unobservable session heterogeneity. Behavioral measures include measures for risk preference (CRRA), cooperation (PGC), and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1) and (3) controls for task performances in tasks 1,2,3 and behavioral measures. Col (2) and (4) add controls for demographic measures. Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$ .

\*\*  $p < 0.05$ .

\*  $p < 0.1$ .

**Table A7**  
Effect of information on tournament in average treatment.

VARIABLES	Task 6 Competition Choice							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average below 37	0.168 (0.106)	0.163 (0.108)						
Average above 37	0.053 (0.054)	0.072 (0.050)						
Average below 40			0.157** (0.074)	0.149** (0.074)				
Average above 40			0.027 (0.064)	0.055 (0.060)				
Average below 41					0.128** (0.063)	0.126** (0.059)		
Average above 41					0.005 (0.079)	0.044 (0.079)		
Average below 42							0.097* (0.058)	0.098* (0.053)
Average above 42							0.038 (0.097)	0.088 (0.100)
Observations	202	202	202	202	202	202	202	202
Demographic controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table reports the marginal effects from probit regressions. The dependent variable is an indicator for choosing Rule-100 (tournament) in Task 6 (yes: 1, no: 0). The Average below 'X' (or above 'X') indicates whether the subjects in the *Average* treatment see the average competition choice in Task 3 as below 'X' percent (or above 'X' percent). Session dummies are included to control for unobservable session heterogeneity. Behavioral measures include measures for risk preference, cooperation, and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1), (3), (5) and (7) control for task performances in tasks 1,2,3; predicted rank and competition choice in Tasks 3; and behavioral measures. Col (2), (4), (6) and (8) additionally control for demographic measures. The 40 % cut-off yields an approximately even split between the "below" and "above" categories. Alternative cut-offs generate more uneven splits, reducing statistical power (see Table A5 for sample sizes across sessions at different values of 'X' in the *Average* treatment) Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$ .

\*\*  $p < 0.05$ .

\*  $p < 0.1$ .

**Table A8**  
Effect of information on change in beliefs about winning in Task 6.

VARIABLES	Average Treatment		Random Treatment	
	Change in beliefs about winning			
	(1)	(2)	(3)	(4)
Average below 40	6.317* (3.621)	7.039* (3.600)		
Average above 40	-1.084 (4.300)	-0.543 (4.385)		
Rule 25			-0.817 (3.621)	-0.157 (3.927)
Rule 100			0.723 (3.526)	0.616 (3.503)
Observations	202	202	205	205
Demographic controls	No	Yes	No	Yes
	<u>Test of Avg Below40=Avg Above40</u>		<u>Test of Rule 25 = Rule 100</u>	
t-statistic	1.553	1.661	-0.372	-0.181
p-value	0.122	0.0983	0.710	0.857

Notes: The table reports the estimated treatment effects at the mean from linear regression. The dependent variable is the difference in predicted probability of winning between Task 6 and Task 3 (reported in percentage probability 1–100). The Average below 40 (or above 40) indicates whether the subjects in the *Average* treatment see the average competition choice in Task 3 as below 40 percent (or above 40 percent). The Rule-100 (or Rule-25) indicates whether the subjects in the *Random* treatment see the choice of the randomly chosen participant in Task 3 as Rule-100 (or Rule-25). Behavioral measures include measures for risk preference, cooperation, and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1) and (3) controls for task performances in tasks 1,2,3 and behavioral measures. Col (2) and (4) add controls for demographic measures. Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$ .

\*\*  $p < 0.05$ .

\*  $p < 0.1$ .

**Table A9**  
Effect of information on switching to competition.

VARIABLES	Average Treatment		Random Treatment	
	Switching from Piece-rate to Competition		(3)	(4)
	(1)	(2)		
Average below 40	0.191*	0.219**		
	(0.110)	(0.097)		
Average above 40	0.072	0.032		
	(0.075)	(0.074)		
Rule 25			0.235**	0.230**
			(0.117)	(0.117)
Rule 100			0.109	0.113
			(0.076)	(0.073)
Task 3 Pred Rank	-0.053	-0.082**	-0.044	-0.037
	(0.034)	(0.040)	(0.034)	(0.037)
Observations	123	123	118	118
Demographic controls	No	Yes	No	Yes

Notes: The table reports the estimated marginal effects at the mean from probit regressions. The dependent variable is an indicator for choosing Rule-100 (tournament) in Task 6 (yes: 1, no: 0) conditional on making an initial choice of piece-rate in Task 3. The Average below 40 (or above 40) indicates whether the subjects in the *Average* treatment see the average competition choice in Task 3 as below 40 (or above 40) percent. The Rule-100 (or Rule-25) indicates whether the subjects in the *Random* treatment see the choice of the randomly chosen participant in Task 3 as Rule-100 (or Rule-25). Session dummies are included to control for unobservable session heterogeneity. Behavioral measures include measures for risk preference, cooperation, and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1) and (3) controls for task performances in tasks 1,2,3 and behavioral measures. Col (2) and (4) add controls for demographic measures. Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$ .

\*\*  $p < 0.05$ .

\*  $p < 0.1$ .

**Table A10**  
Effect on pay-off of switching from piece-rate to competition.

VARIABLES	T6 Payoff	
	(1)	(2)
P2C	-13.76	-6.710
	(276.5)	(288.9)
Average	-3.027	-3.474
	(17.34)	(19.49)
Random	-17.34	-12.62
	(23.78)	(29.51)
P2C x Average	20.35	-0.106
	(316.1)	(328.5)
P2C x Random	69.20	55.89
	(345.6)	(348.3)
Task 3 Pred Rank	-15.09	-15.32
	(16.98)	(18.19)
Constant	176.9	532.0
	(120.4)	(449.8)
Observations	185	185
Demographic controls	No	Yes

Notes: The table reports the estimated effects from OLS. The dependent variable is the earnings (payoff) from Task 6. P2C is an indicator if the participants switched from a piece-rate choice in task 3 to tournament choice in Task 6. Session dummies are included to control for unobservable session heterogeneity. Behavioral measures include measures for risk preference, cooperation, and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1) controls for task performances in tasks 1,2,3, and behavioral measures. Col (2) includes controls for demographic measures. Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$ .

\*\*  $p < 0.05$ .

\*  $p < 0.1$ .

**Table A11**  
Gaps in competition choice by gender.

VARIABLES	Task 3 Competition Choice				Task 6 Competition Choice			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.218*** (0.061)	-0.160*** (0.061)	-0.087 (0.060)	-0.045 (0.062)	-0.142** (0.063)	-0.100 (0.062)	0.011 (0.061)	0.043 (0.064)
Task 3 Performance		0.022* (0.012)	-0.001 (0.012)	0.001 (0.012)				
Task 3 Pred Rank			-0.248*** (0.028)	-0.256*** (0.028)				
Task 6 Performance						0.046*** (0.011)	0.024** (0.011)	0.027** (0.011)
Task 6 Pred Rank							-0.217*** (0.037)	-0.218*** (0.036)
Observations	307	307	307	303	307	307	307	303
Task Performance	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Behavioral Measures	No	No	No	Yes	No	No	No	Yes
Demographic controls	No	No	No	Yes	No	No	No	Yes

Notes: The table reports the estimated marginal effects at the mean from probit regressions. The dependent variable is an indicator for choosing Rule-100 (tournament) in Task 3 for Columns 1–4 and in Task 6 for Columns 5–8. Session dummies are included to control for unobservable session heterogeneity. Behavioral measures include measures for risk preference, cooperation, and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1) and (5) do not include any controls. Col (2) and (6) controls for task performances in tasks 1,2, and 3. Col (3) and (7) add controls for predicted ranks. Col (4) and (8) add controls for behavioral and demographic measures. Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$ .

\*\*  $p < 0.05$ .  
\*  $p < 0.1$ .

**Table A12**  
Probit regression with gender and treatment interactions.

VARIABLES	Average Treatment		VARIABLES	Random Treatment	
	(1)	(2)		(3)	(4)
Average	0.246 (0.276)	0.312 (0.277)	Random	0.200 (0.244)	0.168 (0.250)
Female	0.071 (0.340)	-0.006 (0.364)	Female	-0.126 (0.329)	-0.166 (0.345)
Female # Average	0.588 (0.492)	0.771 (0.527)	Female # Random	0.333 (0.520)	0.316 (0.534)
Task 3 Pred Rank	-0.570*** (0.171)	-0.721*** (0.183)	Task 3 Pred Rank	-0.339** (0.165)	-0.328** (0.158)
Task 3 Choice	1.667*** (0.255)	1.761*** (0.259)	Task 3 Choice	1.394*** (0.238)	1.493*** (0.249)
Observations	202	202	Observations	205	205
Behavioral Measures	Yes	Yes	Behavioral Measures	Yes	Yes
Demographic controls	No	Yes	Demographic controls	No	Yes

Notes: The table reports the estimated effects from probit regressions. The dependent variable is an indicator for choosing Rule-100 (tournament) in Task 6 (yes: 1, no: 0). The bottom panel of the table reports the predicted probability of choosing Rule-100 (tournament) in Task 6 for each of the treatment-gender groups. Session dummies are included to control for unobservable session heterogeneity. Behavioral measures include measures for risk preference, cooperation, and optimism. Demographic controls include age, gender, religion, caste, previous academic records, and work experience. Col (1) and (3) controls for task performances in tasks 1,2,3 and behavioral measures. Col (2) and (4) add controls for demographic measures. Robust standard errors are reported in parentheses. \*\*\*  $p < 0.01$ .

\*\*  $p < 0.05$ .  
\*  $p < 0.1$ .

## Appendix B

## Screen 8: Section 1 : Task 1.1 - Rule 25

Time left to complete this page: 1:54

Add the smallest number in left matrix and the smallest number in right matrix and enter in the corresponding box.

- |    |    |    |
|----|----|----|
| 67 | 68 | 88 |
| 50 | 86 | 25 |
| 66 | 50 | 68 |

71	76	38
6	50	9
98	40	70
- |    |    |    |
|----|----|----|
| 81 | 98 | 47 |
| 13 | 65 | 31 |
| 72 | 92 | 56 |

4	54	85
32	94	33
61	97	42
- |    |    |    |
|----|----|----|
| 94 | 56 | 62 |
| 82 | 11 | 57 |
| 65 | 57 | 86 |

41	53	42
9	54	8
89	78	66
- |    |    |    |
|----|----|----|
| 98 | 60 | 76 |
| 19 | 79 | 51 |
| 93 | 71 | 16 |

34	69	95
6	80	51
46	35	88

Fig. B1. Screenshot of the addition task.

Notes: The subjects are required to pick the smallest numbers from each of the two matrices, add the two smallest numbers, and enter the sum in the space provided. The score for each task is decided by the number of correct answers entered Fig. B2.

## Screen 20: Information

**We provide some information about decisions made in Task 1.3:  
Some participants chose Rule 100 while others chose Rule 25.**

Next

(a) Screenshot of information provided in the *Control* treatment.

## Screen 20: Information

**We provide some information about decisions made in Task 1.3:  
The percentage of participants who chose Rule 100 is <xx> %.**

Next

(b) Screenshot of information provided in the *Average* treatment.

## Screen 20: Information

**We provide some information about decisions made in Task 1.3:  
One randomly chosen participant chose Rule<xx>.**

Next

(c) Screenshot of information provided in the *Random* treatment.

**Fig. B2.** Screenshot of information provided before task 6 by treatment groups.

Notes: The figure shows the screen viewed by participants in each treatment group about the tournament choices from the baseline round i.e. Task 3 (this was called Task 1.3 during the experiment session). This screen was shown to participants before Task 6. The screenshots presented here are from pilot sessions.

## Appendix C

### Instructions

[Click here for complete set of experimental instructions](#)

#### Demographics

1. Date of Birth:
2. Gender:
3. Caste Category: GEN / OBC / SC /ST
4. Religion: Hindu / Muslim / Sikh / Christian / Jain / Buddhist / Others
5. Marital Status: married / Unmarried
6. Father's highest level of education: Primary / Secondary / Class 10 / Class 12 / Graduate / Post-Graduate / Above Post-Graduate
7. Mother's highest level of education: Primary / Secondary / Class 10 / Class 12 / Graduate / Post-Graduate / Above Post-Graduate
8. Your Marks in Class 10:
9. Your marks in Class 12:
10. Your Previous Level of Education:
11. CAT Score:
12. Previous Work Experience:

**Optimism**<sup>26</sup> (Life Orientation Test (Scheier et al., 1994))

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1. In uncertain times, I usually expect the best.					
2. It's easy for me to relax.					
3. If something can go wrong for me, it will.					
4. I'm always optimistic about my future.					
5. I enjoy my friends a lot.					
6. It's important for me to keep busy.					
7. I hardly ever expect things to go my way.					
8. I don't get upset too easily.					
9. I rarely count on good things happening to me.					
10. Overall, I expect more good things to happen to me than bad.					

**Appendix D**

**Proof. of Proposition 1.**

The total payoff from piece-rate is independent of the belief about competition and is given by  $pa_i$ , where  $i \in \{L, H\}$ . On the other hand, the expected payoff from tournament entry is a decreasing function of the underlying belief and is given by  $ca_i f_i(\mu), i \in \{L, H\}$  with  $f_H(\mu) > f_L(\mu) \forall \mu \in [0, 1]$ . Fig. D1 below shows the payoff function under piece-rate and tournament schemes for both high ability and low ability individuals.

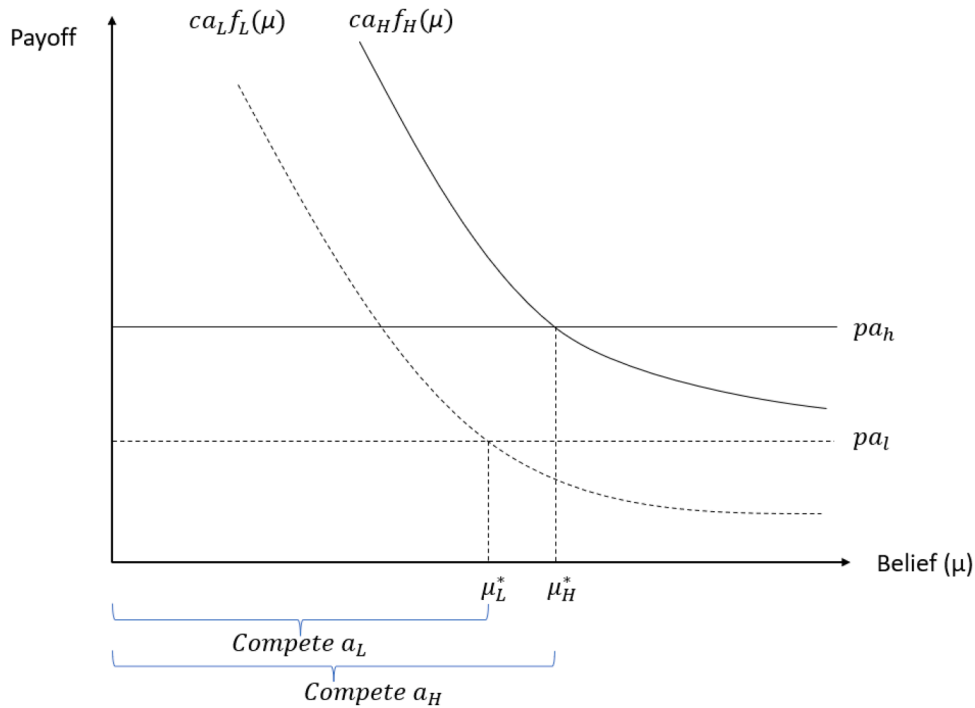


Fig. D1. Model equilibrium.

Agents choose to enter competition if the expected payoff from the tournament is higher than the piece-rate payoff. We can define the cut-off belief as the point where the agent is indifferent between piece-rate and tournament choice. Thus, the cut-off beliefs,  $\mu_L^*$  and  $\mu_H^*$  are as follows:

$$pa_L = ca_L f_L(\mu_L^*),$$

$$pa_H = ca_H f_H(\mu_H^*)$$

<sup>26</sup> For each of the items, the options strongly disagree to strongly agree are coded integer values 0 to 4 respectively. For the measure of optimism, mean of items 1, 3, 4, 7, 9 and 10 is taken after reverse coding items 3, 7 and 9. Items 2, 5, 6 and 8 are fillers and not scored.

Simplifying further, we can show that

$$\mu_L^* = f_L^{-1}\left(\frac{P}{C}\right),$$

$$\mu_H^* = f_H^{-1}\left(\frac{P}{C}\right).$$

Since  $f_L(\cdot)$  and  $f_H(\cdot)$  are strictly decreasing functions, the cut-off beliefs  $\mu_L^*$  and  $\mu_H^*$  are unique for high ability and low ability agents. Further, since  $f_H(\mu) > f_L(\mu) \forall \mu \in [0, 1]$ ,  $f_H^{-1}(\cdot) > f_L^{-1}(\cdot)$  implying  $\mu_H^* > \mu_L^*$ .

**Proof. of Corollary 1.1.**

Let  $n(a_i, \mu)$  be the measure of individuals with ability  $i \in \{L, H\}$  and belief  $\mu \in [0, 1]$ . Since high ability and low ability agents are distributed similarly over the beliefs, we assume  $n(a_H, \mu) = n(a_L, \mu), \forall \mu \in [0, 1]$ . Then, the total measure of low ability individuals choosing competition is given by  $\int_0^{\mu_L^*} n(a_L, \mu) d\mu$ , while the corresponding measure for high ability is  $\int_0^{\mu_H^*} n(a_H, \mu) d\mu$ . Since we already know that  $\mu_H^* > \mu_L^*$  and  $n(\cdot, \mu)$  is equal for both  $a_H$  and  $a_L$ , higher measure of high ability individuals participate in the tournament compared to low ability agents.

**Proof. of Proposition 2.**

Let us consider the case of  $\frac{k}{N} < \mu$  where we need to prove that  $\frac{k}{N} < \tilde{\mu} < \mu$ . We will proceed in 2 steps.

*Step 1: Prove  $\tilde{\mu} < \mu$  using contradiction.*

Suppose this is not true. We already know that  $\mu = \frac{\alpha}{\alpha+\beta}$  while  $\tilde{\mu} = \frac{\alpha+k}{\alpha+\beta+N}$ . Thus,

$$\frac{\alpha+k}{\alpha+\beta+N} \geq \frac{\alpha}{\alpha+\beta}$$

Simplifying this, we arrive at

$$\frac{k}{N} \geq \frac{\alpha}{\alpha+\beta}$$

which is a contradiction. Hence  $\tilde{\mu} < \mu$ .

*Step 2: Prove  $\frac{k}{N} < \tilde{\mu}$  using contradiction.*

Suppose not. Then,

$$\frac{\alpha+k}{\alpha+\beta+N} \leq \frac{k}{N}$$

Simplifying this, we arrive at the same contradiction

$$\frac{k}{N} \geq \frac{\alpha}{\alpha+\beta}$$

Thus,  $\frac{k}{N} < \tilde{\mu}$  and hence  $\frac{k}{N} < \tilde{\mu} < \mu$ . We can repeat the same proof to generate the converse result.

**Proof. of Proposition 3.**

Consider the first case  $\frac{k}{N} < \mu_L^*$ . From proposition 2, we know that all agents with belief  $\mu > \frac{k}{N}$  will reduce their belief about competition. Since  $\mu_L^* > \frac{k}{N}$ , all agents with belief  $\mu > \mu_L^*$  will update their beliefs towards lower competition, thus shifting their beliefs to the left. Thus, there exists an  $\epsilon_L$  neighbourhood around  $\mu_L^*$  such that, low ability agents with beliefs higher than the cut-off, i.e.,  $\mu \in (\mu_L^*, \mu_L^* + \epsilon_L)$  will update their belief to below the cut-off such that  $\tilde{\mu} < \mu_L^*$ , thus entering the competition. Hence, among low ability agents,

competition choice will increase by at least  $\int_{\mu_L^*}^{\mu_L^* + \epsilon_L} n(a_L, \mu) d\mu$ , where  $n(a_L, \mu)$  is the measure of low ability agents with belief  $\mu$ . Similarly,

among high ability individuals, competition choice will increase by at least  $\int_{\mu_H^*}^{\mu_H^* + \epsilon_H} n(a_H, \mu) d\mu$ . Thus, there is an increase in competition choice among both low and high ability agents.

By similar logic, we can prove the other two cases. When  $\frac{k}{N} > \mu_{H}^*$ , then all agents with beliefs less than  $\frac{k}{N}$  will increase their belief about competition. Thus, there exists at least one group of low ability agents with beliefs  $\mu \in (\mu_L^* - \epsilon_L, \mu_L^*)$ , and high ability agents with beliefs  $\mu \in (\mu_H^* - \epsilon_H, \mu_H^*)$ , who will choose to leave the competition. Thus, there is a decline in competition among both high and low ability individuals.

Finally, when  $\mu_L^* < \frac{k}{N} < \mu_H^*$ , there exists  $\epsilon_L$  and  $\epsilon_H$  such that, low ability agents with beliefs  $\mu \in (\mu_L^* - \epsilon_L, \mu_L^*)$  update their belief to be greater than  $\mu_L^*$ , while high ability agents with beliefs  $\mu \in (\mu_H^*, \mu_H^* + \epsilon_H)$  shift their belief to be less than  $\mu_H^*$ . Thus, there is a decrease in competition among low ability, but an increase in competition among high ability individuals.

**Proof. of Corollary 3.1.**

Suppose there are 2 observed competition scenarios,  $k_1$  and  $k_2$ , such that  $k_1 < k_2$ . Then the updated beliefs satisfy

$$\frac{\alpha + k_1}{\alpha + \beta + N} < \frac{\alpha + k_2}{\alpha + \beta + N}$$

Thus, in the scenario with lower competition, agents reduce their belief more than the other scenario. Since this is true for all  $\alpha$  and  $\beta$ , it leads to more agents crossing the cut-off beliefs (both  $\mu_H^*$  and  $\mu_L^*$ ), and thus entering the competition.

**Proof. of Corollary 3.2.**

Let's first consider the case of individuals shifting from piece-rate to competition, after observing that the overall competition is  $k/N$ . Individuals who make this switch update their prior belief about competition from above the cut-off ( $\mu_H^*$  for high ability and  $\mu_L^*$  for low ability) to below the cut-off. Let  $(\mu_H^* + \epsilon_H)$  be the upper bound on the belief of a high ability individual who end up switching to competition. Similarly, let  $(\mu_L^* + \epsilon_L)$  be the highest belief of a low ability agent who switches to competition. From our assumption of a Beta prior, the cut-off beliefs  $\mu_H^*$  and  $\mu_L^*$  satisfy

$$\mu_H^* = \frac{\alpha_H^*}{\alpha_H^* + \beta_H^*}, \quad \mu_L^* = \frac{\alpha_L^*}{\alpha_L^* + \beta_L^*}.$$

As mentioned in the main text, we can interpret the Beta parameter  $\alpha$  as the prior belief about number of people choosing competition and  $\beta$  as the number of people choosing piece-rate. Hence,  $\alpha_H^* + \beta_H^* = \alpha_L^* + \beta_L^* = N$ . This implies,

$$\mu_H^* = \frac{\alpha_H^*}{N}, \quad \mu_L^* = \frac{\alpha_L^*}{N}.$$

Since we already know  $\mu_H^* > \mu_L^*$ , we can infer that  $\alpha_H^* > \alpha_L^*$ . Similarly, the maximum belief among high ability and low ability individuals who end up switching to competition is given by  $\frac{\alpha_H^* + \epsilon_H}{N}$  and  $\frac{\alpha_L^* + \epsilon_L}{N}$  respectively.

Among the switchers, the upper bound on the belief can be defined as that level, such that, after receiving information on the total competition  $k/N$ , the updated belief is exactly equal to the cut-off belief. Thus, we can define  $\epsilon_H$  and  $\epsilon_L$  as

$$\frac{\alpha_H^* + \epsilon_H + k}{2N} = \frac{\alpha_H^*}{N},$$

$$\frac{\alpha_L^* + \epsilon_L + k}{2N} = \frac{\alpha_L^*}{N}.$$

Simplifying further, we can show that

$$\epsilon_H = \alpha_H^* - k, \quad \epsilon_L = \alpha_L^* - k.$$

Since  $\alpha_H^* > \alpha_L^*$ , we get  $\epsilon_H > \epsilon_L$ . Assuming similar distribution of high ability and low ability agents over the beliefs, the total number of switchers satisfy

$$\int_{\mu_H^*}^{\mu_H^* + \epsilon_H} n(a_H, \mu) d\mu > \int_{\mu_L^*}^{\mu_L^* + \epsilon_L} n(a_L, \mu) d\mu,$$

as  $\epsilon_H > \epsilon_L$ . Thus, for a given observed level of competition, more high ability individuals switch from piece-rate to competition compared to low ability individuals.

We can use a similar logic to prove the converse result. Among agents switching from competition to piece-rate, we can show that

$$\epsilon_H = k - \alpha_H^*, \quad \epsilon_L = k - \alpha_L^*.$$

Thus,  $\epsilon_L > \epsilon_H$ , which implies more low ability agents shift from competition to piece-rate compared to high ability agents.

**Proof. of Proposition 4.**

We proceed with this proof in two steps. First, we show that agents observing that all  $N > 1$  individuals choosing competition will update their beliefs a lot more compared to those seeing a single person choosing competition. Next, we quantify a bound on the signal

strength i.e., the minimum number of people (out of  $N$  agents) who must choose competition for this result to hold.

*Step 1: Observing all  $N$  choosing competition.*

The initial belief of an agent is  $\frac{\alpha}{\alpha+\beta}$ . The updated belief when this agent observes all the others choosing competition is given by

$$\tilde{\mu}_N = \frac{\alpha + N}{\alpha + \beta + N}$$

The updated belief when the agent just observes a random individual choosing competition is given by

$$\tilde{\mu}_1 = \frac{\alpha + 1}{\alpha + \beta + 1}$$

We need to prove  $\tilde{\mu}_N > \tilde{\mu}_1$ . Suppose not. Then,  $\frac{\alpha+N}{\alpha+\beta+N} \leq \frac{\alpha+1}{\alpha+\beta+1}$ . Solving this, we get

$$\beta N \leq \beta$$

which is a contradiction as  $N > 1$ . Thus,  $\tilde{\mu}_N > \tilde{\mu}_1$ .

*Step 2: Bound on signal strength*

We now solve for the minimum proportion of competition required for this result to hold. We solve for the cut-off  $\gamma$  that satisfies

$$\frac{\alpha + N/\gamma}{\alpha + \beta + N} = \frac{\alpha + 1}{\alpha + \beta + 1}$$

where  $1/\gamma$  refers to the proportion of competition  $k/N$ . Solving this, we can derive

$$\frac{1}{\gamma} = \frac{(\alpha + 1)N + \beta}{N(\alpha + \beta + 1)}$$

$1/\gamma$  is the minimum proportion of competition  $k/N$  required for an individual to update their belief more than the random information.<sup>27</sup>

Till now, we analysed the choice of competition. But this result holds true for the choice of piece-rate as well. We can again repeat the analysis as follows.

*Step 1: Observing all  $N$  choosing piece-rate.*

The updated belief of observing all  $N$  choosing piece-rate is

$$\tilde{\mu}_N = \frac{\alpha + 0}{\alpha + \beta + N}$$

The updated belief when they observe a random individual choosing piece-rate is

$$\tilde{\mu}_1 = \frac{\alpha + 0}{\alpha + \beta + 1}$$

We can immediately see that,  $\tilde{\mu}_N < \tilde{\mu}_1$ . Thus, agents reduce their belief more when they observe all  $N$  choosing piece-rate, compared to a random observation.

*Step 2: Bound on signal strength*

We now solve for the minimum proportion of piece-rate choice (or the maximum proportion of competition) required for this result to hold. We solve for the cut-off  $\gamma$  that satisfies

$$\frac{\alpha + N/\gamma}{\alpha + \beta + N} = \frac{\alpha + 0}{\alpha + \beta + 1}$$

Solving this, we can derive

$$\frac{1}{\gamma} = \frac{\alpha(N - 1)}{N(\alpha + \beta + 1)}$$

<sup>27</sup> Assuming  $\alpha$  and  $\beta$  to be 5 and 45 respectively, and  $N$  to be 50, we get  $1/\gamma$  to be 0.135. Thus, an individual need to observe at least 13.5 % of the people choosing competition in order to update their belief more than the random information.

$1/\gamma$  is the maximum proportion of competition  $k/N$  for an individual to update their belief more than the random information. Equivalently,  $(1 - 1/\gamma)$  is the minimum proportion of piece-rate choice required for this result to hold.<sup>28</sup>

### Proof. of Lemma 1.

Since agents with high perceived ability  $\hat{a}$  (and hence high  $\gamma$ ) believe that they can solve more problems correctly, they believe that they have a higher probability of winning the tournament. Hence, decision to enter the tournament is increasing in  $\hat{a}$  (and  $\gamma$ ). Let  $T(\gamma) \in \{0, 1\}$  denote the tournament choice as a function of  $\gamma$ . Since  $G(\gamma|a = a_H)$  FOSD  $G(\gamma|a = a_L)$ , and  $T(\gamma)$  is increasing in  $\gamma$ , this implies

$$Pr(\text{enter} | a = a_H) = \mathbb{E}(T(\gamma)|a = a_H) \geq \mathbb{E}(T(\gamma)|a = a_L) = Pr(\text{enter} | a = a_L).$$

Hence, high ability agents are more likely to enter the tournament compared to low ability agents.

### Data availability

Data will be made available on request.

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<sup>28</sup> Assuming  $\alpha$  and  $\beta$  to be 45 and 5 respectively, and  $N$  to be 50, we get  $(1 - 1/\gamma)$  to be 0.135. Thus, the agent will respond more to average information compared to random information as long as at least 13.5 % of the people choose piece-rate.

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