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Martín Brun

The Complexity of Being Fair

Tampere University
UNIVERSITY OF HELSINKI
VATT INSTITUTE FOR ECONOMIC RESEARCH
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Martín Brun†

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We explore whether complexity shape which fairness views people follow. We report findings from a lab-in-the-field experiment conducted with school students aged 10 to 15, a sample with significant cognitive variation and a uniform background. In the experiment, participants decide how to distribute earnings between workers who completed tasks under unequal opportunities. First, we examine whether differences in cognitive ability predict which fairness rules people follow. We find that more able participants are more likely to follow meritocratic fairness views and prefer to compensate workers based on effort. The difference is driven by those who account for the unequal opportunities workers experience (a more complex decision rule), coinciding with a decline in egalitarian responses (a simpler decision rule). Second, we analyze the procedural aspects of the decisions. We show that more able individuals are better equipped to handle the counterfactual inferences needed to account for unequal opportunities. A between-subject manipulation shows that providing this step closes the decision gap within meritocrats, whose decision rules differ only in the use of that step, with the treatment effect concentrated in low able individuals. These findings highlight the role of procedural choice in distribution decision-making and underscore cognition as an additional determinant of fairness pluralism.

JEL-Classification: D91, D63, D83, D84.

Keywords: fairness, complexity, cognitive ability, inequality of opportunities, children.

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†Tampere University, FIT - Finnish Centre of Excellence in Tax Systems Research, and EQUALITAS - Economics of Inequality and Poverty Analysis. Contact: martin.brun@tuni.fi.

1 Introduction

Fairness views play a crucial role in shaping people's acceptance of inequality. The prevailing view in western societies is meritocratic (Alesina and Angeletos, 2005; Almås et al., 2020, 2025; Stantcheva, 2021), by which inequalities arising from personal choices are deemed to be more fair than those resulting from lucky circumstances (Cappelen et al., 2007, 2013; Konow, 2000).[1] However, choices are rarely detached from circumstances. For example, effort exertion adjusts in response to the incentives that individuals face (Altmejd et al., 2021; Bursztyn et al., 2017; Falk et al., 2022; Glover et al., 2017; Parsons et al., 2011). Although most people acknowledge this, only part of them try to correct the resulting inequalities (Andre, 2025; Bhattacharya and Mollerstrom, 2025; Cappelen et al., 2024; Preuss et al., 2025).

We propose that complexity and procedural choice can help explain this puzzle. A long tradition in economics (e.g., Simon, 1955; Tversky and Kahneman, 1974) argues that people dislike (or are incapable of) implementing complex rules and procedures. We understand fairness views as different decision rules for distributing outcomes, and these vary in complexity. For example, an *egalitarian* view, which treats all inequalities as unfair (e.g., Rawls, 1971; Temkin, 1993), prescribes a simple rule: split outcomes equally between individuals. By contrast, *meritocratic* views, which accept inequalities resulting from choices, require assessing each individual's decision. Within these views, some rules even consider the circumstances that shaped decisions (e.g., Roemer, 1993).[2] Taking into account this latter step is more complex: it demands more information processing steps and imposes higher cognitive costs (Johnson and Payne, 1985; Newell and Simon, 1972; Oprea, 2025; Payne et al., 1993).

In this paper, we study the extent to which complexity determines the fairness rules people follow. We approach this question in two ways: by examining whether differences in available cognitive resources, proxied by cognitive ability, predict which fairness rules people follow,[3] and by testing the effects of experimental manipulations in the cognitive demands to apply different rules. Together, these approaches let us assess complexity-driven fairness pluralism directly, and make progress toward understanding the cognitive processes behind it.

To measure the cross-sectional relationship between fairness views and cognitive ability, we conducted a lab-on-the-field experiment in a Uruguayan private full-day school. Participants comprise students aged 10 to 15, a period of intense cognitive changes (Steinberg, 2005).[4] Focusing on this sample allows us

[1] This ideal is closely intertwined with the notion of equality of opportunity, which often contrasts with reality. Various empirical works show that individual's income, educational attainment, and overall life outcomes tend to be closely tied to their family background (Akee et al., 2019; Becker et al., 2018; Chetty et al., 2014; Chetty and Hendren, 2018; Corak, 2013).

[2] The common idea among this view is that people should not accept inequalities arising from factors beyond individual responsibility. Dworkin (1981a,b) argue that equalization efforts should focus in initial circumstances rather than in outcomes. Arneson (1989) and Cohen (1989) defend individual responsibility as a morally legitimate source of inequality. Roemer (1998) defines equality of opportunities as a situation in which individuals exerting equal effort are entitled to equal outcomes, and any inequality due to circumstances beyond their control should be eliminated.

[3] We consider two distinct ways cognitive ability can relate to fairness views. First, a subject's cognitive ability may limit the maximum information they can process. Second, it may proxy how much information they are willing to process. In either case, we expect similar effects on the fairness views people follow. In this paper, we do not aim to determine which of these two mechanisms is at work.

[4] Brain develops throughout early adolescence, both in structure and function. White-to-gray matter ratio alters, multiple regions of the prefrontal cortex grow, and linkages on the whole brain expand rapidly (Paus, 2005). These changes focus on areas that are particularly relevant for executive functioning (Giedd et al., 1999), and result in marked improvements in

to address a major identification challenge: that personal upbringing context may shape both fairness views (Almås et al., 2016; Cohn et al., 2023; Cunha et al., 2010; Jakiela et al., 2015; Kosse et al., 2020; Hvidberg et al., 2023) and cognitive development (Carneiro et al., 2021; Cunha and Heckman, 2007; Cunha et al., 2010; Heckman, 2008; Kautz et al., 2014). These participants share similar educational experiences and socio-economic background: most entered the school at kindergarten, have received all their formal education there, live in the surrounding neighborhoods, and lack material deprivations. These features provide a clean group to explore how fairness views evolve with cognitive development, as there is limited scope for confounding impact of different upbringing context.

In the experiment, we ask participants to act as third-party spectators (Cappelen et al., 2007, 2013), and evaluate how to reward choices made under different circumstances. We follow Andre (2025) and introduce a situation in which two real, but unknown, workers complete effort tasks for a piece-rate payment. Their circumstances are their exogenously determined piece-rate payments.[5] The lucky worker is assigned a high piece-rate payment (10 points per task completed), while the unlucky worker is assigned a low one (1 point per task completed). The incentive difference yields a significant impact, as the task completion of the lucky worker doubles that of the unlucky one, and result in a 20-to-1 earnings difference. The spectators have to decide how to distribute the earnings within the pair, with full information about workers' circumstances, choices, and generated earnings. We elicit stated and revealed preferences separately. Stated preferences are directly asked. We distinguish between the most prominent fairness views: *egalitarianism*, *libertarianism*, and *meritocratic* fairness view, disentangling between those that account for unequal opportunities (*comparable choice meritocrats*) or those who don't (*actual choice meritocrats*). Revealed preferences are derived from the actual decisions, and precede preference statements. This sequential approach allows us to identify both each participant's fairness view and how they implement it, which supports the second part of our analysis. After the decision phase is over, we apply a Raven's Standard Progressive Matrices test (Raven, 1936, 2000), a well-validated and age-appropriate test for measuring cognitive ability that (in various versions) has been widely used in the economic literature (see e.g., Gill and Prowse, 2016; Lambrecht et al., 2024; Proto et al., 2019, 2022).

We find that higher cognitive ability is associated with a larger following of complex fairness views. In particular, the share of participants stating to be meritocrats is 13 percentage points higher among those whose Raven's test scores are in the upper half of the distribution. The difference with the lower half is almost entirely explained by a larger share of comparable choice meritocrats (i.e., the most cognitively demanding fairness view), and coincides with a 10 p.p. decline in the egalitarian view (i.e., the simplest view). We confirm that these stated preferences are indicative of actual decisions.[6] We also show that spectators' reasoning aligns with their fairness views. Participants are asked to explain their judgments,

reasoning and information processing (Keating, 2004).

[5] Throughout the paper, we use circumstances and opportunities interchangeably, as the circumstances in our setting determine the incentive structure and thus the opportunities to exert effort.

[6] Spectators that declare to be egalitarians assign the unlucky worker the largest share, approaching equality. Libertarians assign the lowest share, closest to the initial distribution. Meritocrats are in between: they partially correct the initial inequality, but do not fully equalize. Among them, counterfactual meritocrats assign a higher share to the unlucky worker. This difference is in line with expected, as this meritocratic view prescribes accounting for the increased effort exertion under favorable circumstances.

and we analyze the concepts they use with natural language processing (NLP) techniques (see e.g., Ash and Hansen, 2023; Gentzkow et al., 2019; Lucchetti and Cajueiro, 2025). We also use a generative large language model (LLM) to classify explanations according to the fairness view they represent and the depth of reasoning they involve (see e.g., Varian, 2014; Ludwig et al., 2025).[7] Our results are in line with previous findings that suggest that children move towards more complex fairness views as they grow up (Almås et al., 2010). We show that these changes account for around 10% of the changes experienced with age, highlighting the role that cognitive ability plays in the development of fairness views.

To directly test for a causal effect of cognitive demands on fairness views implementation, we conduct between-subject interventions within the experiment. We focus on a specific information processing step: the inference on the impact of the circumstances on effort exertion. This step has some interesting features. First, it is challenging for our participants. Accuracy is low in our sample, with participants underestimating how circumstances affect effort exertion. On average, they infer 26% more effort exertion under high piece-rate payment, which is much below the 100% observed in worker's choices. Most able participants are more precise (inferring a 17 p.p. larger change, p-value=.015), but equally uncertain on their inferences (diff.=4.3 p.p., p-value=.435). Second, not all decision rules require solving this step.[8] Only meritocrats need to consider the effort exerted by each worker, and within them, only comparable choice meritocrats account for the impact of opportunities on their decisions.

In our first intervention, we solve this step. Participants receive additional information on worker's choice for an equal circumstance scenario.[9] The manipulation yields a statistically significant increase in assignments to the unlucky worker, but only among actual choice meritocrats (19% above the mean, p-value= .008). We find no effect among comparable choice meritocrats or non-meritocrats. These results are consistent with procedural decision-making, as solving the step only affects those whose decisions would have otherwise stopped at the previous step. Notably, the manipulation closes the assignment gap between the two types of meritocrats, whose decision rules differ only in the use of that step. An alternative explanation relates to uncertainty aversion (as in Andre, 2025; Cappelen et al., 2022), as uncertainty is removed by this manipulation. Although our design does not allow us to disentangle these explanations, the lack of variation in confidence about inferences suggests that this channel is unlikely to account for our findings. In our second intervention, we draw attention towards this step. Participants are asked to elicit their beliefs about worker's choice for an equal circumstance scenario. The manipulation yields no effect on participants following any fairness view, stressing the relevance of actually solving the step.

[7] Participants' explanations differ in the use of key aspects. Egalitarians stress equality, libertarians earnings, and meritocrats tasks and effort. Among meritocrats, comparable choice meritocrats are more likely to mention luck. We further compute LLM-generated assessment of the explanations provided. We find, on average, that the highest scores are in the view stated by participants, and that meritocrats provide the most sophisticated responses.

[8] Egalitarians always split equally, irrespective of any information about the workers. Libertarians only need information on the outcomes produced by each worker.

[9] The intervention manipulates the complexity of the task itself to identify its role in behavior. This type of intervention has been commonly used, for example to studying risk decisions (as in Bernheim and Sprenger, 2020; Bohren et al., 2024; Enke and Graeber, 2023; Puri, 2025).

Related literature. Our work builds and contributes to the vast literature of fairness and inequality acceptance (e.g., Almås et al., 2020; Cappelen et al., 2007, 2013; Konow, 2000; Stantcheva, 2021). These studies show that a significant share of people are sensitive to the source of inequalities. We focus on a recent extension that distinguishes within meritocrats and we complement this literature by testing behavioral underpinnings for such division. Considering the impact of circumstances over choices implies belief formation, which makes for more complex decision-making. Our main finding shows that the prevalence of a fairness view that accounts for it increases alongside cognitive ability, as people find it less costly to implement it.

Two strands of this literature are closest to our study. One of them finds that people only account partly for unequal opportunities on distribution decisions (Andre, 2025; Bhattacharya and Mollerstrom, 2025; Cappelen et al., 2024; Preuss et al., 2025). Proposed explanations include uncertainty aversion, belief biases, and lack of recognition that circumstance-dependent effort is morally relevant. Our work contributes to this literature in several aspects. First, we provide behavioral underpinnings for the (lack of) prevalence of comparable choice meritocrats. Our findings suggest that procedural complexity deters some people from adhering to that fairness view, and that cognitive resources facilitates its following. We also underscore previous results on uncertainty aversion, showing that while information provision on counterfactual choice is sufficient for changing distribution decisions, making the unequal circumstances salient is not. Second, we explore how such meritocratic views develop as children grow up, and connect it to cognitive development and fairness views complexity. Third, we introduce a method to measure fairness views that is consistent with decisions, and allows to assess implementation consistency at the individual level.

The other strand of the literature analyzes the development of social preferences in children (Almås et al., 2010; Fehr et al., 2008, 2013; Martinsson et al., 2011; Sutter et al., 2018). One important message from these studies is that fairness views evolve throughout childhood (Schunk and Zipperle, 2023). We complement this literature by connecting these changes with age-appropriate and validated measurements of cognitive ability. We provide direct evidence that meritocrats increase alongside cognitive development. Our results also extend this literature by further disentangling meritocratic views in two types: actual choice meritocrats and comparable choice meritocrats. We show that the fairness view which is more complex to implement is more prevalent among more able children, drawing again attention to the role of cognition on fairness pluralism.

Our work also relates to the experimental literature on the behavioral effects of complexity (de Clippel et al., 2025; Gabaix and Graeber, 2024; Gabaix, 2025; Martínez-Marquina et al., 2019; Oprea, 2020; Reverberi et al., 2022). This literature shows that complexity costs determine procedural choices (Arrieta and Nielsen, 2025; Banovetz and Oprea, 2023). Importantly, these costs vary across individual cognitive ability and so does the decision rules they select. For instance, this has been used to explain social behavior in strategic environments (Jones, 2014; Neyman, 1985; Rubinstein, 1986). Our finding that fairness views that subscribe more complex rules are more prevalent among most able people extends this literature to non-strategic environments. We also add to recent explorations on the connection between non-standard behaviors and complexity (Enke et al., 2025; Oprea, 2024). A common thread is that complexity causes insensitivity (Abeler and Jäger, 2015; Enke and Graeber, 2023). We observe a similar pattern for the impact of unequal circumstances, expanding the results into social behavior.

Organization. The remainder of the paper is structured as follows. Section 2 describes the experiment design and its implementation. Section 3 shows our main findings. Section 4 concludes.

2 Experimental Details

The experiment is designed to measure how views concerning the distribution of earnings between individuals who faced unequal opportunities change alongside cognitive ability. We also conduct between-subject manipulations to test causal effects of cognitive demands in shaping these distributive decisions.

The experiment consists of two phases. In the Workers phase, an independent sample of adult workers perform simple effort tasks for earnings. In the Spectator phase, a sample of spectators observe the situation, state their fairness views, and make decisions that can affect the final earnings of workers. The focus of the analysis is on the spectators. The workers are only recruited to create realistic economic conditions.[10]

2.1 Workers Phase

2.1.1 Experimental procedures

Workers complete a simple effort task, based on letter-to-number encryption (Benndorf et al., 2019).[11] They have to translate letter into numbers, based on an encryption table. Progress to the next encryption is only allowed if the encryption is done correctly. There is no limited time or opportunities to answer.

Before the task begin, we inform workers about two possible piece-rates per encryption: a low piece-rate of 1 points (π^L, equivalent to \$0.06), and a high piece-rate of 10 points (π^H, equivalent to \$0.60). We ask workers to commit a number of tasks for each piece-rate ($p_i(\pi^L)$ and $p_i(\pi^H)$ for each worker i). Following commitments, each worker is randomly assigned one of the piece-rates, and they need to follow up on their commitment for the selected piece-rate. This design allows us to know the effort choices of each worker for both low and high piece-rates.

2.1.2 Implementation

We recruited 40 participants on *Prolific* for the Worker phase. Participants were offered a \$2.50 completion payment and could earn additional payoffs for each successfully completed encryption. On average, they completed 15.9 tasks ($\overline{p} = 15.9$, $\mathrm{SD} = 14.5$) and earned \$8.55. Workers committed significantly more tasks for the high piece-rate than for the low piece-rate ($\overline{p(\pi^H)} = 23.1$, $\overline{p(\pi^L)} = 11.8$, difference $= 11.3$,

[10] See Appendices B and C for summaries of each phase, respectively.

[11] We implement the experiment using the oTree platform (Chen et al., 2016). We use a letter-to-number encryption task, with randomization in the encryption table after each round. The task has many advantages that make it suitable for our experiment: it is a simple and easy to explain, it needs no preexisting knowledge, it reduces the scope for guessing to a minimum, and it minimizes learning. Workers are first shown the task instructions and an example. We inform them that the earnings they generate on completing the task can be later influenced by a third party. To avoid distortion on effort decisions due to anticipation, we restrict information about when, how, why, and who is involved in the earnings decision.

p-value = .002). Half of the workers were assigned to the low piece-rate, and the other half to the high piece-rate. After all workers completed the tasks, we formed 20 pairs. Each pair consists of one worker assigned to the low piece-rate (which we refer to as unlucky in the analysis) and one worker assigned to the high piece-rate (which we refer to as lucky).

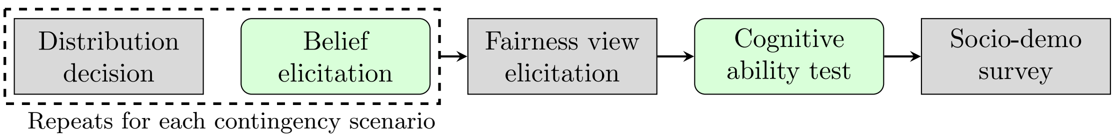
2.2 Spectators Phase

2.2.1 Experimental procedures

Spectators state their views on how to distribute earnings between pairs of workers and make decisions that can actually determine worker's final earnings. Prior to the experiment, we lay out the workers phase setting and briefly explain the role the spectators will have. This introduction is read aloud in each session. The complete instructions are provided to each participant on the computer screens.[12]

The basic experiment flow is depicted in Figure 1. We present five contingency scenarios. In each scenario, participants decide how to distribute earnings and report their beliefs on the impact of unequal circumstances on effort exertion. After the scenarios, we ask participants about their fairness view. Then, we administer a cognitive ability test. Finally, we collect socio-demographic information from participants.

Figure 1: Experiment Flow



Notes: This figure depicts the experiment flow for the spectator phase. Distribution decisions and beliefs elicitation repeat in each contingency scenario. Boxes filled in green are parts of the experiment in which participants can increase their chances of earning additional prizes.

Fairness views. Spectators decide how to split the earnings generated by two workers in a pair. All pairs are formed by one unlucky worker (assigned the low piece-rate) and one lucky worker (assigned the high piece-rate). We employ a strategy method (Selten, 1967; Brandts and Charness, 2011). Spectators decide in five contingency scenarios, each with a unique worker pair. Spectators are informed that their decisions can have real consequences. We randomly select 20 spectator decisions. This implies that 1 in 10 spectators makes a decision with real consequences.[13]

We provide the same type of information in all scenarios. We show assigned piece-rates, effort choice for the assigned piece-rate (i.e., tasks completed), and initial point earnings of each worker in the pair. All

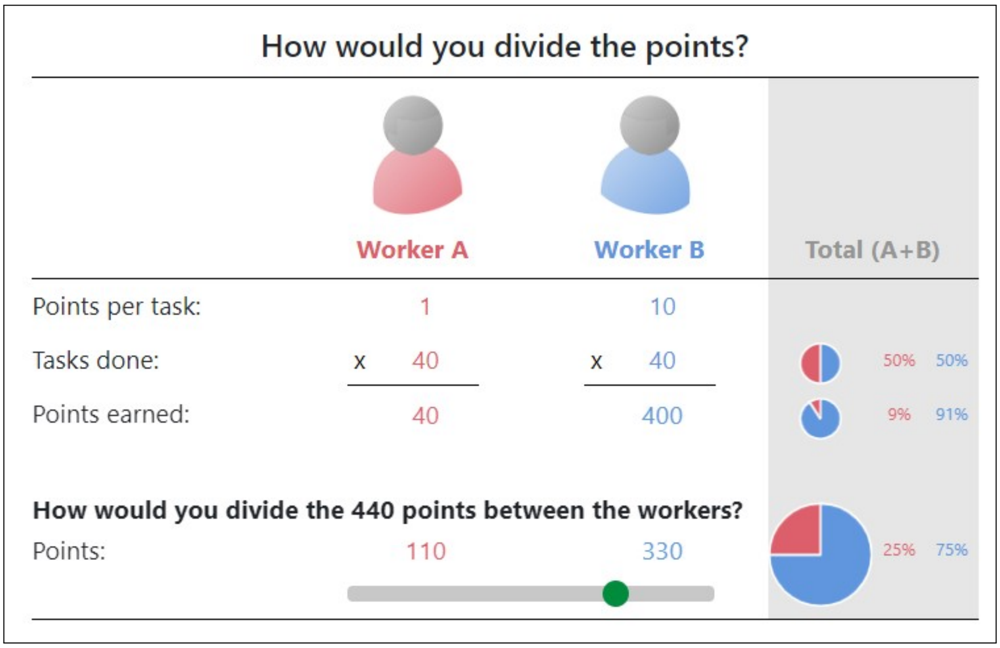
[12] We implement the experiment using using the oTree platform (Chen et al., 2016). We further verify that all spectators understood the setting by asking comprehension questions. We only allow participation after all comprehension questions are correctly answered. Instructed teachers are present in the room to provide explanations if required at any part of the study. We later asked spectators to report their perceived understanding of the instructions. None of the participants in our sample reported a lack of understanding. Over 80% reported to understand mostly all. We show our main results are robust to excluding those who failed to understand at least part of the instructions (see Section 3).

[13] We announce that one of the five contingency scenarios involves a real worker pair, and that decisions for the real pair can be implemented after a lottery. The last scenario is always a real worker pair from the workers phase. The preceding scenarios are hypothetical, and displayed in random order. Spectators are not informed which scenario is real and which are hypothetical.We later asked spectators to guess which of the scenario they are presented is real. Responses for each scenario are all around the share selected by chance (20%). The share for the correct guess is 12%.

information is displayed using simple visual interface, tailored for children. Spectators decide by selecting which share of the total earnings of the pair each worker would get. Decisions are made with a slider, and aided by a dynamic graph (see Figure 2 for a representation of the decision screen).[14]

After spectators make their distribution decisions, we show them one randomly chosen decisions. We ask spectators to explain the reasoning behind the decision, in an open-ended form. Next, we ask spectators about their preferred rule for dividing the points within pairs (i.e., to state their fairness view). We present a close list, with simple statements referring to what should be considered. Spectators have to select one out of four options presented in random order: half and half (*egalitarism*), points contributed (*libertarianism*), tasks completed (*actual choice meritocracy*), and tasks workers would have completed for the same piece-rate (*comparable choice meritocracy*). This final question was incorporated after the pre-registration was filed. We present the results derived because the measure aligns closely with our core research goals and provides highly informative insights.

Figure 2: Distribution Decision Screen



Notes: This figures exemplifies the distribution decision screen, translating from the original screen with text in Spanish. The figure shows a pair of workers. Each worker is depicted as a person and shown with a distinctive color. Piece-rate payment, tasks completed, and initial earnings for each worker are provided. Individual earnings are shown following the layout typically used when teaching multiplication to children. Shares for tasks and earnings are automatically computed and displayed using pie charts. Participants can modify the allocation by moving the slider. A dynamic pie chart updates with the spectator's decision.

Beliefs. Spectators report their beliefs on workers' task commitment for equal piece-rates. We ask these questions in all five scenarios. The reference piece-rate for the belief elicitation is randomly chosen (i.e.,

[14] The visual design was created with input from local teachers. The focus was on making the information easy to understand, and the interface intuitive to use. Consulting teachers are not related to the school where the experiment took place, and were not informed about the research's objectives. Following ethical guidelines, spectators decide on a setting in which earnings is shown as points. The use points also allows for simplifying numbers for children. We explain spectators that the points will be converted into money at the end of the experiment, but do not disclose the conversion rate.

either low or high) for each scenario. Spectators can see all the information provided in the distribution decision screen, including the commitment of the worker assigned the reference piece-rate (see Figure C.4 for a representation of the belief elicitation screen). We ask spectators to estimate how many tasks the worker not assigned to the reference piece-rate would have completed if assigned to it. We also ask participants their certainty about the estimates. Performance is incentivized. Spectators increase their chances of receiving additional prizes if their guess is close to the correct answer.

Cognitive ability. Participants complete the Raven's Standard Progressive Matrices test (Raven, 1936, 2000). This test is a non-verbal assessment used to measure cognitive ability, which (in various versions) has been used to analyze social behavior (e.g., Gill and Prowse, 2016; Lambrecht et al., 2024; Proto et al., 2019, 2022). The test comprises 12 items. Each item consists of a 3x3 matrix with a missing cell. Participants are asked to select the missing cell out of eight choices provided (see Figure C.5 for an item example). Participants receive the test instructions before it begins, and answer a small set of comprehension questions. These refer to the test time limit, number of correct options per item, and an illustrative item (previously used in the instructions). The test only begins after all comprehension questions are correctly answered. Performance is incentivized. Participants increase their chances of earning additional prizes if they answer correctly. The items in the test are presented in increasing difficulty order. Participants are able to navigate back and forth throughout the test to review and modify their answers as needed. The test lasts up to 6 minutes. All unanswered items are considered incorrect.

Socio-demographic survey. Participants answer a survey on age, gender, neighborhood of residence, and other socio-demographic questions. There is no time limit to answer this survey.

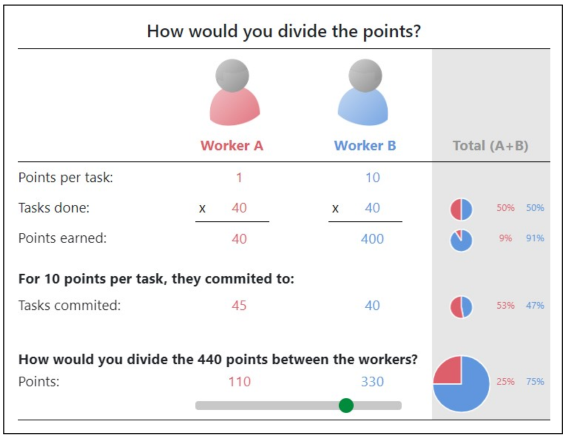
Treatment conditions. We randomly assign spectators to different treatment conditions in a between-subject design. Only the tasks for contingency scenarios vary across treatments. The control group (`T0`) is as previously detailed. Participants receive information on assigned piece-rates, effort choice for the assigned piece-rate, and initial earnings of each worker in the pair. Participants first decide on how to distribute earnings, and then elicit beliefs on the impact on unequal circumstances on effort exertion. The first treatment group (`T1`) completes the tasks in the same order, but receives additional information for the distribution decisions. Participants also receive information on the effort choice for the non-assigned piece-rate (see Figure C.2). The second treatment group (`T2`) receives the same information for the distribution decisions, but completes the tasks in inverted order. Participants first elicit beliefs on the impact on unequal circumstances on effort exertion, and then decide on how to distribute earnings. Both treatment groups aim to alter the inference on the impact of piece-rate assignment on effort exertion. While the first intervention (in `T1`) practically solves the inference at the agent-level, the second intervention (in `T2`) primes participants to think about it.

2.2.2 Implementation

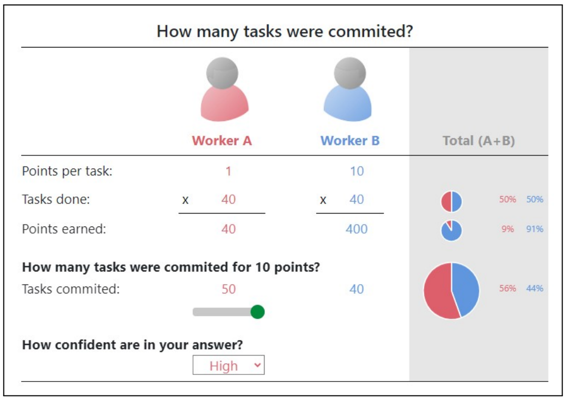
We invite school students to be spectators, in collaboration with a private full-day school in Montevideo, Uruguay. The project was granted ethical approval by the UAB Ethics Committee on Animal and Human

Figure 3: Screens Featured in the Interventions

(a) Decision with Additional Information



(b) Belief Elicitation



Notes: These figures exemplify the distribution decision and belief elicitation screens, translating from the original screen with text in Spanish. Subfigure (a) shows the decision screen with additional information used in T1. The screen is similar to the one depicted in Figure 2, with an additional line showing the task commitment for a same piece-rate payment. This piece-rate payment is randomly selected for each pair. Subfigure (b) shows the belief elicitation screen. Participants are randomly shown task commitments for a reference piece-rate, and asked to guess for the worker non-assigned the reference piece-rate. Participants can modify their inference by moving the slider. All treatment arms feature belief elicitation. In T2, belief elicitation precedes the distribution decisions.

Experimentation and the executive board of the school. Parents of involved students received a consent form asking for approval for their children to participate. All parents gave their consent. Children were also instructed that their participation was voluntary. None refused to participate. In accordance to ethical guidelines, participants were offered prize baskets consisting of school canteen products worth 75 Uruguayan Pesos (∼ \$2.00) and could earn additional prizes (worth up to 265 Uruguayan Pesos, ∼ \$7.00).[15]

We recruited 198 participants. The sampling plan was preregistered, as working with this sample allows us to hold constant many schooling and socio-economic factors that might otherwise confound the analysis.[16] The experiment was conducted throughout four days on September 2023. Sessions took place during regular school hours at the computer lab and lasted 40 minutes. Attendance was high for all groups (see Table C.1). As we run the experiment during regular school hours and all attending students participating, there is no self-selection. After completing the surveys, participants were thanked and dismissed. Participants picked-up their rewards when leaving. Rewards were delivered in sealed bags anonymously, based on the number assigned to the computer where the experiment is implemented. The average value of the prize basket reward was 113 Uruguayan Pesos (∼ \$3.00).

[15] The consent form received by the parents contained information on the project and the rewards for the children, with an explicit school endorsement. No specific details on the tasks or aim of the research was communicated. The minimum prize for participants is worth more than 2 days of average daily canteen expenditure in our sample, while the maximum prize is worth more than 8 days. Average daily canteen expenditure within the sample is 32.5 Uruguayan Pesos (∼ \$0.87), with low variance. Additional prizes are bundled together in different types of baskets, with each basket offering escalating rewards. See Appendix B for more details in the spectator phase payments.

[16] Spectators were aged between 10 and 15, and mostly live in the neighborhoods surrounding the school. Most students entered the school for kindergarten between ages 2 and 5, and had received their entire formal education at the school. Table C.2 in the Appendix compares characteristics of our sample with the city's population. Given the observed characteristics, it is reasonable to believe that spectators reside in households on the right part of the income distribution. Moreover, households are much homogenous in their lack of limitations to provide material conditions for appropriate cognitive development.

3 Results

3.1 Cross-sectional Analysis

Table 1 summarizes the findings of the cross-sectional analysis. Column 1 presents the stated fairness views in our sample. Meritocracy is the most common view. Close to three quarters of the participants (75.8%) declare to follow a meritocratic fairness view. The remaining participants are split between egalitarianism (13.1%) and libertarianism (11.1%). Meritocrats are further split into two groups: actual choice meritocrats and comparable choice meritocrats. Actual choice meritocrats value the efforts actually exerted. They represent 51.0% of the sample. Comparable choice meritocrats consider the efforts that would have been exerted under equal circumstances. They account for 24.7% of the sample.[17]

Table 1: Fairness Views and Cognitive Ability

	Total	Low CA	High CA	Diff.	CA coef.
	(1)	(2)	(3)	(4)	(5)
Panel A. Main fairness views					
Egalitarian	.131	.165	.067	-.099**	-.052**
				(.045)	(.025)
Meritocrat	.758	.711	.840	.129**	.077**
				(.059)	(.032)
Libertarian	.111	.124	.093	-.031	-.025
				(.045)	(.025)
Panel B. Within Meritocrats					
Actual choice	.510	.512	.520	.008	.023
				(.074)	(.036)
Comparable choice	.247	.198	.320	.122*	.055*
				(.065)	(.031)

Notes: This table reports fairness view shares. Columns (1) refers to the whole sample. Columns (2) to (4) distinguishes by cognitive ability. Groups are formed based on the median of the cognitive ability measurement. The first group (low) has scores below the median. The second group (high) has scores above the median. Columns (2) and (3) report the share of each fairness view in each group. Columns (4) reports the difference between the two groups. Columns (5) reports estimates of cognitive ability on fairness views. The dependent variables are valued 1 for each stated fairness view, and 0 otherwise. The independent variable is the standardized cognitive ability test score. Each row reports estimates from a linear model. Robust standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

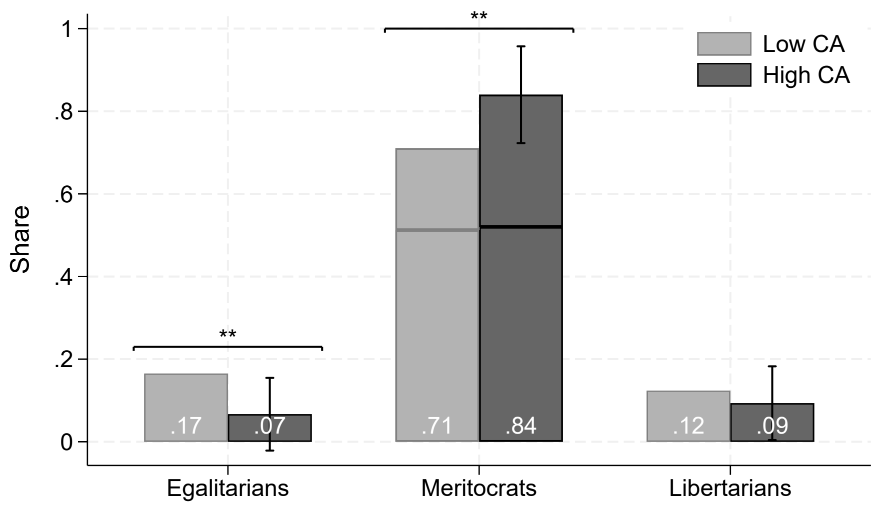
We leverage Raven's test scores to explore the role of cognitive ability in predicting participant's fairness views. We split the sample into two groups by the median test score, and estimate the share differential for the most able group. Columns 2 to 4 of Table 1 and Figure 4 shows our main findings. Meritocrats are more common among most able. We estimate that being in the upper half of the cognitive ability test scores is associated with a 12.9 p.p. larger likelihood of following meritocratic fairness views, a statistically (p-value=.031) and economically significant effect (17% increase compared to the base rate).

[17] Our sample has remarkably large share of meritocrats when compared with previous literature. Almås et al. (2025) estimate the share of egalitarians, meritocrats, and libertarians for adult population in 60 countries using a design with equal opportunities. In similar countries (e.g., Argentina, Chile, and Brazil) meritocrats represent just below 50% of the population. Within populations, Almås et al. (2016) show that meritocracy is larger among those from high socio-economic context as our sample. Moreover, in a context with unequal opportunities similar to our study Andre (2025) estimates a 68% share of meritocrats for adults in the United States.

In turn, egalitarians are much less common among the most able. Their share more than halves (-9.9 p.p., p-value=.028). Libertarians remain rather stable (-3.1 p.p., p-value=.499).

Our setting allows us to further disentangle within the meritocratic fairness view. The share of actual choice meritocrats (reported in Panel B of Table 1 and plotted as the lower bar within meritocrats in Figure 4) shows no change by cognitive ability (0.8 p.p., p-value=.918). The overall increase in meritocrats is entirely explained by the larger share of comparable choice meritocrats among the most able (12.2 p.p., p-value=.064). This rise is particularly relevant, as it represents a 49% expansion compared to the base rate.

Figure 4: Fairness Views and Cognitive Ability



Notes: This figure presents estimates of cognitive ability on fairness views. The light bar plots fairness view shares among participants scoring below the median in the cognitive ability measurement. The dark bar plots shares for participants scoring above the median in the cognitive ability measurement. Meritocrats are further split in both groups by a line: the lower bars represent actual choice meritocrats and the upper bar represents comparable choice meritocrats. The error spikes correspond to the 95% confidence interval as estimated via ordinary least squares regression with robust standard errors. Differences in proportions are statistically significant at the 10% level using Fisher's exact test (p-value = .082), Pearson's chi-squared test (p-value = .085), and Likelihood-ratio chi-squared test (p-value = .071). * $p < .10$, ** $p < .05$, *** $p < .01$

Demographic variation. There are some demographic differences that can confound our analysis. The major sources of demographic variation are age, current schooling grade, and gender.[18] The remaining scope for heterogeneity is reduced, as individuals share socioeconomic and educational context.

Our experiment focuses on participants aged 10 to 15. The selection of this age range is motivated by physical brain changes (e.g., growth in prefrontal regions, shifts in white-to-gray matter, and expanding neural connections) that enhance executive functioning and drive age-related gains in cognitive ability. In our sample, a one-year age increase is associated with a 3.8 p.p. higher score in the Raven's test score

[18] Schooling grade is largely explained by age (R^2=.891). The non-explained variation can respond to several reasons. Entry grade is based on calendar year (i.e., children born in the same year start school together), which creates age differences within a given grade. In addition, students who started in other schools may follow different cutoff dates (e.g., the public system cutoff date is in April), and some students may have repeated a grade. The results are much in line with variations in age. We omit the schooling grade based analysis for brevity.

(p-value<.001). The sample is composed, in rather similar size, by boys and girls. Girls account for 44% of the total, and outperform boys in the test by 5.9 p.p. (p-value=.034).

Table 2 explores how fairness views change alongside these variables. We focus on egalitarian and meritocratic fairness views, as libertarianism is not correlated with cognitive ability (β =-.025, p-value=.322, see column 5 in Table 1). Age correlates with these fairness views. Younger children tend to be more egalitarian, and place less weight on merit. Our results align with Almås et al. (2010), who study children of similar ages in Norway and find that egalitarianism dominates at younger ages but declines sharply as meritocratic views increase.[19] We can further account that cognitive ability explains about 10% of these changes (8% of the drop in egalitarianism, and 14% of the rise in meritocraticism). Gender, in turn, does not correlate with these fairness views (-4.2 p.p. for boys, p-value=.392 on egalitarianism; -1.3 p.p. for boys, p-value=.834 on meritocracy).

Table 2: The Role of Cognitive Ability

	Egal.			Merit.		
	(1)	(2)	(3)	(4)	(5)	(6)
Age	-.063***		-.058***	.057***		.045**
	(.018)		(.018)	(.021)		(.022)
Sex		-.042			-.013	
		(.049)			(.062)	
CA			-.028			.058*
			(.024)			(.034)
Dep. var. mean	.128	.128	.128	.760	.760	.760
Explanation	-	-	8%	-	-	14%
Observations	196	196	196	196	196	196
R^2	.078	.004	.084	.038	.000	.055

Notes: This table reports estimates of demographic characteristics on egalitarian and meritocratic fairness views. The dependent variables are valued 1 for each stated fairness view, and 0 otherwise. Age is measured in integer years, and sex is valued 1 for boys and 0 for girls. CA is the standardized cognitive ability test score. Each column reports estimates from a linear model. Robust standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Robustness checks. We test the robustness of the results to different analysis decisions.

Participant's comprehension. One plausible explanation of the difference in stated fairness views is that more able participants have a better understanding of the instructions. We take several steps to ensure that all participants understand the experimental instructions, in order to avoid that channel (see Appendix B for a detailed description of the procedures). To further check that lack of comprehension is not driving the results, we ask participants about their degree of understanding of the instructions after they decide. None of the participants report not understanding the instructions, and most report almost

[19] There are some differences between our design and that of Almås et al. (2010). In our experiment, decisions refer to a situation marked by unequal circumstances that directly influence effort exertion. In Almås et al. (2010), the unequal circumstances affect piece-rate payments only after effort is exerted, which makes all meritocratic fairness views to prescribe the same decision rule.

complete understanding (over 80%). We replicate the main analysis excluding participants who failed to understand part of the instructions (see Table A.4). Results are robust to this exclusion.

Cutoff thresholds. Our main results are based on splitting the sample into two groups by the median (a score of 8 out of a maximum of 12). To check the robustness of the results to this choice, we estimate differences for different cutoffs (see Table A.5). We split groups by cognitive ability using scores of 7 and 9 as the cutoff for high cognitive ability. The share of comparable choice meritocrats is higher among the high cognitive ability group, but only significant for the group defined by the higher cutoff. We also estimate the correlation between following each fairness view and the standardized score of the cognitive ability test (see column 5 in Table 1). A 1 SD higher score is associated with a 5.2 p.p. less probability of following egalitarianism (p-value=.037), 7.7 p.p. more of following meritocracism (p-value=.017), and 5.5 p.p. for the case of comparable choice meritocracism (p-value=.078).

Experimental manipulations. Our cross-sectional analysis is based in the data collected for participants in all treatment arms. In case our interventions impact fairness views, the results would be affected. To check the robustness of the results to it, we replicate the main analysis only using the control group (see Table A.6). The results are very similar to the ones in our main analysis: egalitarians are 11.2 p.p. less prevalent in the high cognition group (p-value=.098), meritocrats rise by 14.4 p.p. (p-value=.159), and comparable choice meritocrats by 23.0 p.p. (p-value=.040). The sample size is more reduced, yielding more noise in the estimates.

Measure validity. We examine the validity of our fairness view measures. We focus on its alignment with decision participants make, and the justifications they provide.

Table 3 reports how decisions and explanations provided by participants align with their stated fairness views. Column 1 shows the mean assignment to the unlucky worker. Egalitarians assign the largest share (44.7% on average), and in 55% of the cases they assign income equally between workers. In contrast, libertarians assign the lowest share to the unlucky worker (21.1% on average), which results in favoring the lucky worker in 91% of the cases. Their explanations often refer to the earnings, which accumulate 13% of the meaningful words they use (see column 5 in Table 3). Meritocrats lie in between, assigning 37.6% to the unlucky worker. They refer extensively to the effort (10% of the meaningful words in use, see column 6 in Table 3). Within meritocrats, those that take into account comparable choices assign more to the unlucky worker (diff.=4.6 p.p., p-value<.001). Their explanations are slightly less referring to effort, and more to luck. We further validate the views by analyzing the explanation with eight LLM agents. For each explanation, we compute indices of alignment with each fairness view and average the LLM agent's output. Column 8 shows the values for the fairness view stated by participants. Overall, the alignment is highest for the view stated by participants. Lastly, we use the LLM agents to gauge the sophistication of the explanations provided and find that explanations by meritocrats are the most complex.

Table 3: External Validity of Fairness Views Measurement

	Assign.	Favored			Concepts used			LLM	
	unlucky	Lucky	None	Unlucky	Earnings	Tasks	Luck	Align.	Soph.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Main fairness views									
Egalitarian	.447	.346	.554	.100	.046	.057	.057	.473	.491
Meritocrat	.376	.653	.283	.064	.089	.100	.040	.493	.620
Libertarian	.211	.909	.064	.027	.133	.082	.031	.347	.519
Panel B. Within Meritocrats									
Actual choice	.361	.685	.277	.038	.088	.104	.035	.531	.612
Comparable choice	.407	.588	.294	.118	.090	.090	.052	.415	.637

Notes: This table reports behavior and explanations provided by fairness view. Columns (1) shows mean assignment share to the unlucky worker. Columns (2) to (4) report qualitative measures of the redistributive decisions. We compute dummy variables valued 1 according to who gets the largest share of the assignment: the lucky worker in column (2), the unlucky worker in column (3), or none in column (4) for decisions that assign each worker between 45% and 55% of the total. Columns (5) to (7) report mean share of words from each concept used over total words in the decision justification. Earnings include: 'points', and verbs 'contribute', 'achieve', 'win'; Effort include: 'tasks', and verbs 'complete', 'fulfill', 'decide', 'effort', 'choose', 'do', 'make"and Luck includes 'luck', 'random', and verbs 'receive', 'get', 'chance', 'would', 'could', 'commit'. Columns (8) and (9) report LLM-generated assessment of the explanations. We ensemble eight Gemini 2.5 agents to compute the indices and report the average of their outputs. Column (9) shows continuous indices of alignment of the explanations with the fairness view stated by the participants. Column (10) shows continuous indices of explanation sophistication.

3.2 Evidence on Behavioral Mechanisms

We explore explanations for our finding that a larger share of more cognitive able people are meritocrats, and take more into account comparable choices for their decisions. We focus on the procedural aspects of the decision. We include indirect evidence that fairness views differ in cognitive requirements in the Annex.[20] We present results from the two between-subject manipulations on the information processing step in the decision-making procedure. We find that solving this step yields a significant effect for meritocrats that normally stop at the preceding step and closes the gap within meritocrats, but priming participants into thinking about it has a null impact.

Comparable choice meritocracy involves a unique step among the fairness views we study: getting information about the effort that would have been exerted by workers in an equal opportunity situation. Participants can infer it or, in this experiment, acquire it by completing a task.[21] Such beliefs, their confidence on them, and the willingness to pay to access information can explain differences in following comparable choice meritocracy.

Table 4 report how these variables change across cognitive ability. More able individuals infer a much higher increase in effort exertion if workers experience high piece-rate payments (compared to low piece-rate payments). They think the unlucky workers response is 67% larger (p-value=.015, column 3 in Table 4). This translates into a lower effort difference in equal opportunity scenarios, and can explain favoring

[20] We show that implementation accuracy varies across fairness views, being lower for decision rules with higher state complexity, and that it is better among those who are more able.

[21] We offer participants the opportunity to complete a task to acquire information. The task is announced after decisions, and is described as an effort task that differs from the one done by the workers (as in Dong et al., 2025). This situation resembles real life, where such type of information is not available, but inputs for estimating it can be obtained at a cost.

Table 4: Cognitive Ability and Behavior

	Implementation error		Beliefs about unlucky worker		Information acquisition
			Δ effort when lucky	Confidence	
	(1)	(2)	(3)	(4)	(5)
High CA	-.023*	-.031**	.171**	.043	.056
	(.014)	(.014)	(.070)	(.055)	(.061)
View FE	No	Yes	No	No	No
Dep. var. mean	.421	.421	.255	.296	.763
Effect magn.	-6%	-7%	67%	14%	7%
Observations	980	980	980	980	980
R^2	.008	.043	.007	.002	.004

Notes: This table reports estimates of cognitive ability on behavior. The independent variable is valued 1 for participants scoring above the median in the cognitive ability test score., and 0 otherwise. Columns (1) and (2) show mean implementation error in absolute terms. Columns (3) and (4) show beliefs about the effort exerted by the unlucky worker. Column (3) shows the effort difference between the situation with high piece-rate payment and low piece-rate payment, and column (4) shows the confidence stated on the belief. Columns (5) shows whether the participant completed an additional task to get information on the effort under equal opportunities, computed as a dummy variable. Each columns reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

comparable choice rather than actual choices as the basis for decisions. In turn, we find no difference in confidence on these beliefs, nor different willingness to acquire precise information.

To causally test whether cheaper access to this information impacts decisions, we compare participants under different treatment conditions. Table 5 presents the estimates. First, we find that solving the inference step increases assignments to the unlucky worker. The effect is entirely driven by actual choice meritocrats, who assign 19% more (p-value=.008, in column 3 of Panel A in Table 5). This result suggests that those following actual choice meritocracy are willing to incorporate information on effort exertion under equal opportunity when its freely accessed. Interestingly, the intervention effects closes the decision gap within meritocrats. These patterns imply that the use of such information can explain behavioral differences within meritocrats. The intervention effect is also driven by low able individuals (18% over the mean, p-value=.011, in column 5 of Panel A in Table 5), supporting the hypothesis that cognitive ability constraints incorporating this step into decisions.

Second, we find no significant results when priming participants to think on the inequality of opportunities previous to their decision (see Panel B in Table 5). These results suggest that solving the step is necessary; inducing participants to focus on the worker's piece-rate inequality is not enough. Completely disentangling the relevance of the cognitive cost of solving the step and the uncertainty involved in the inference is beyond the scope of our experimental design. Cappelen et al. (2022) shows that uncertainty prevents meritocrats to decide based on counterfactuals. Our first experimental manipulation solves this uncertainty, and yields effects in line with this finding. However, we collect information suggesting that uncertainty can only be part of these findings. Low and high able participants in our sample do not differ in uncertainty about their beliefs (diff.=4.3 p.p., p-value=.435, see column 4 in Table 4), leaving only differential unobservable uncertainty aversion as an explanation to that hypothesis.

Table 5: Intervention Effects on Redistributive Decisions

	Assignment to unlucky worker					
Subsample:	Egal.	Comp.	Act.	Libe.	Low CA	High CA
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Solving state						
`T1`: Solving	.015	-.006	.068***	-.024	.065**	.005
	(.042)	(.033)	(.025)	(.068)	(.025)	(.038)
Dep. var. mean	.447	.414	.364	.214	.374	.363
Effect magn.	3%	-1%	19%	-11%	18%	1%
Observations	85	180	335	80	435	235
R^2	.107	.072	.095	.060	.078	.048
Panel B. Priming state						
`T2`: Priming	.001	-.019	.015	-.016	.004	.014
	(.049)	(.041)	(.030)	(.066)	(.033)	(.035)
Dep. var. mean	.446	.405	.344	.22	.346	.371
Effect magn.	0%	-5%	4%	-7%	1%	4%
Observations	85	145	360	80	400	265
R^2	.079	.125	.056	.089	.046	.056

Notes: This table reports the treatment effects on assigned share to the unlucky worker. The dependent variable is computed as the assignment to the unlucky worker as a share of total earnings in each worker pair. The independent variables are treatment condition dummies. Panel A reports the treatment effects for solving the inference step (`T1`), compared with the control group (`T0`). Panel B reports the treatment effects for priming participants into thinking about inference step (`T2`), compared with the control group (`T0`). Columns (1) to (4) cover spectators following each fairness view. Columns (5) to (5) cover spectators by cognitive ability. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4 Conclusion

We study how cognitive complexity shapes the fairness rules people follow. Our results show that individuals with higher cognitive ability are more likely to follow fairness views that require more demanding reasoning steps. In particular, meritocrats who account for how unequal circumstances affect effort are more prevalent among more able participants. Experimental manipulations further support a causal role of complexity: simplifying the inference step that links circumstances to effort shifts behavior toward more complex fairness views, while merely drawing attention to it does not.

These findings suggest that fairness pluralism partly reflects cognitive constraints. Simpler fairness views, such as egalitarian or libertarian ones, are easier to implement, while more sophisticated meritocratic views impose higher processing demands. Differences in assessment capacity may influence individual moral decisions, potentially leading to sub-optimal collective outcomes. Unlike disagreements rooted in pure preferences, disagreements arising from complexity can be mitigated through targeted interventions. Our results indicate that informational campaigns or procedural simplifications can help individuals make decisions that fully incorporate relevant information, improving social welfare.

More broadly, our study highlights that cognitive constraints shape both individual fairness judgments and collective responses to inequality. This has implications for interpreting social preferences from observed choices: what appears as a simple preference may reflect bounded cognitive capacity rather than moral conviction. It also suggests that skill development, through education or training, can enhance the implementation of more complex fairness rules. Finally, our findings provide a framework for awareness campaigns and public policy communication, emphasizing the role of cognitive support in fostering decision-making.

References

Abeler, J., Falk, A., Goette, L., and Huffman, D. (2011). "Reference Points and Effort Provision". *American Economic Review* 101(2): 470–92. DOI: 10.1257/aer.101.2.470.

Abeler, J., and Jäger, S. (2015). "Complex Tax Incentives". *American Economic Journal: Economic Policy* 7(3): 1–28. DOI: 10.1257/pol.20130137.

Akee, R., Jones, M. R., and Porter, S. R. (2019). "Race Matters: Income Shares, Income Inequality, and Income Mobility for All U.S. Races". *Demography* 56(3): 999–1021. DOI: 10.1007/s13524-019-00773-7.

Alesina, A., and Angeletos, G.-M. (2005). "Fairness and Redistribution". *American Economic Review* 95(4): 960–980. DOI: 10.1257/0002828054825655.

Almås, I., Cappelen, A. W., Salvanes, K. G., Sørensen, E. Ø., and Tungodden, B. (2016). "Fairness and family background". *Politics, Philosophy & Economics* 16(2): 117–131. DOI: 10.1177/1470594X15618966.

Almås, I., Cappelen, A. W., Sørensen, E. Ø., and Tungodden, B. (2010). "Fairness and the Development of Inequality Acceptance". *Science* 328(5982): 1176–1178. DOI: 10.1126/science.1187300.

Almås, I., Cappelen, A. W., Sørensen, E. Ø., and Tungodden, B. (2025). "Fairness Across the World". NHH Department of Economics Discussion Paper 06.

Almås, I., Cappelen, A. W., and Tungodden, B. (2020). "Cutthroat Capitalism versus Cuddly Socialism: Are Americans More Meritocratic and Efficiency-Seeking than Scandinavians?". *Journal of Political Economy* 128(5): 1753–1788. DOI: 10.1086/705551.

Altmejd, A., Barrios-Fernández, A., Drlje, M. et al. (2021). "O Brother, Where Start Thou? Sibling Spillovers on College and Major Choice in Four Countries". *Quarterly Journal of Economics* 136(3): 1831–1886. DOI: 10.1093/qje/qjab006.

Andre, P. (2025). "Shallow Meritocracy". *Review of Economic Studies* 92(2): 772–807. DOI: 10.1093/restud/rdae040.

Arneson, R. (1989). "Equality and equal opportunity for welfare". *Philosophical Studies* 56: 159–194.

Arrieta, G., and Nielsen, K. (2025). "Procedural Decision-Making In The Face Of Complexity".

Ash, E., and Hansen, S. (2023). "Text Algorithms in Economics". *Annual Review of Economics* 15(1): 659–688. DOI: 10.1146/annurev-economics-082222-074352.

Banovetz, J., and Oprea, R. (2023). "Complexity and Procedural Choice". *American Economic Journal: Microeconomics* 15(2): 384–413. DOI: 10.1257/mic.20210032.

Becker, G. S., Kominers, S. D., Murphy, K. M., and Spenkuch, J. L. (2018). "A Theory of Intergenerational Mobility". *Journal of Political Economy* 126(S1): S7–S25. DOI: 10.1086/698759.

Benndorf, V., Rau, H. A., and Sölch, C. (2019). "Minimizing learning in repeated real-effort tasks". *Journal of Behavioral and Experimental Finance* 22: 239–248. DOI: 10.1016/j.jbef.2019.04.002.

Bernheim, B. D., and Sprenger, C. (2020). "On the Empirical Validity of Cumulative Prospect Theory: Experimental Evidence of Rank-Independent Probability Weighting". *Econometrica* 88(4): 1363–1409. DOI: 10.3982/ecta16646.

Bhattacharya, P., and Mollerstrom, J. (2025). "Lucky to Work". *Review of Economics and Statistics*: 1–44. DOI: 10.1162/rest.a.259.

Bohren, J. A., Hascher, J., Imas, A., Ungeheuer, M., and Weber, M. (2024). "A Cognitive Foundation for Perceiving Uncertainty". DOI: 10.3386/w32149, NBER Working Paper No. 32149.

Brandts, J., and Charness, G. (2011). "The strategy versus the direct-response method: a first survey of experimental comparisons". *Experimental Economics* 14(3): 375–398. DOI: 10.1007/s10683-011-9272-x.

Bursztyn, L., Fujiwara, T., and Pallais, A. (2017). "'Acting Wife': Marriage Market Incentives and Labor Market Investments". *American Economic Review* 107(11): 3288–3319. DOI: 10.1257/aer.20170029.

Cappelen, A. W., Hole, A. D., Sørensen, E. Ø., and Tungodden, B. (2007). "The Pluralism of Fairness Ideals: An Experimental Approach". *American Economic Review* 97(3): 818–827. DOI: 10.1257/aer.97.3.818.

Cappelen, A. W., Konow, J., Sørensen, E. Ø., and Tungodden, B. (2013). "Just Luck: An Experimental Study of Risk-Taking and Fairness". *American Economic Review* 103(4): 1398–1413. DOI: 10.1257/aer.103.4.1398.

Cappelen, A. W., Liu, Y., Nielsen, H., and Tungodden, B. (2024). "Fairness in a Society of Unequal Opportunities". NHH Department of Economics Discussion Paper 17.

Cappelen, A. W., Mollerstrom, J., Reme, B.-A., and Tungodden, B. (2022). "A Meritocratic Origin of Egalitarian Behaviour". *Economic Journal* 132(646): 2101–2117. DOI: 10.1093/ej/ueac008.

Carneiro, P., López García, I., Salvanes, K. G., and Tominey, E. (2021). "Intergenerational Mobility and the Timing of Parental Income". *Journal of Political Economy* 129(3): 757–788. DOI: 10.1086/712443.

Chen, D. L., Schonger, M., and Wickens, C. (2016). "oTree—An open-source platform for laboratory, online, and field experiments". *Journal of Behavioral and Experimental Finance* 9: 88–97. DOI: 10.1016/j.jbef.2015.12.001.

Chetty, R., and Hendren, N. (2018). "The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects". *Quarterly Journal of Economics* 133(3): 1107–1162. DOI: 10.1093/qje/qjy007.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014). "Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States". *Quarterly Journal of Economics* 129(4): 1553–1623. DOI: 10.1093/qje/qju022.

de Clippel, G., Moscariello, P., Ortoleva, P., and Rozen, K. (2025). "Caution in the Face of Complexity". Unpublished Working Paper.

Cohen, G. A. (1989). "On the Currency of Egalitarian Justice". *Ethics* 99(4): 906–944. DOI: 10.1086/293126.

Cohn, A., Jessen, L. J., Klašnja, M., and Smeets, P. (2023). "Wealthy Americans and redistribution: The role of fairness preferences". *Journal of Public Economics* 225: 104977. DOI: 10.1016/j.jpubeco.2023.104977.

Corak, M. (2013). "Income Inequality, Equality of Opportunity, and Intergenerational Mobility". *Journal of Economic Perspectives* 27(3): 79–102. DOI: 10.1257/jep.27.3.79.

Cunha, F., and Heckman, J. (2007). "The Technology of Skill Formation". *American Economic Review* 97(2): 31–47. DOI: 10.1257/aer.97.2.31.

Cunha, F., Heckman, J. J., and Schennach, S. M. (2010). "Estimating the Technology of Cognitive and Noncognitive Skill Formation". *Econometrica* 78(3): 883–931. DOI: 10.3982/ECTA6551.

Dong, L., Huang, L., and Lien, J. W. (2025). "'They Never had a Chance': Unequal Opportunities and Fair Redistributions". *Economic Journal* 135(667): 914–942. DOI: 10.1093/ej/ueae099.

Dworkin, R. (1981a). "What is Equality? Part 1: Equality of Welfare". *Philosophy & Public Affairs* 10(3): 185–246.

Dworkin, R. (1981b). "What is Equality? Part 2: Equality of Resources". *Philosophy & Public Affairs* 10(4): 283–345.

Enke, B., and Graeber, T. (2023). "Cognitive Uncertainty". *The Quarterly Journal of Economics* 138(4): 2021–2067. DOI: 10.1093/qje/qjad025.

Enke, B., Graeber, T., and Oprea, R. (2025). "Complexity and Time". *Journal of the European Economic Association* 23(5): 1838–1867. DOI: 10.1093/jeea/jvaf009.

Falk, A., Kosse, F., and Pinger, P. (2022). "Mentoring and Schooling Decisions: Causal Evidence". DOI: 10.2139/ssrn.3635177, CESifo Working Paper No. 8382.

Fehr, E., Bernhard, H., and Rockenbach, B. (2008). "Egalitarianism in young children". *Nature* 454(7208): 1079–1083. DOI: 10.1038/nature07155.

Fehr, E., Glätzle-Rützler, D., and Sutter, M. (2013). "The development of egalitarianism, altruism, spite and parochialism in childhood and adolescence". *European Economic Review* 64(1): 369–383. DOI: 10.1016/j.euroecorev.2013.09.006.

Gabaix, X. (2025). "A Theory of Complexity Aversion". unpublished working paper. DOI: 10.2139/ssrn.5185671.

Gabaix, X., and Graeber, T. (2024). "The Complexity of Economic Decisions". DOI: 10.2139/ssrn.4505599, NBER Working Paper 33109.

Gentzkow, M., Kelly, B., and Taddy, M. (2019). "Text as Data". *Journal of Economic Literature* 57(3): 535–574. DOI: 10.1257/jel.20181020.

Giedd, J. N., Blumenthal, J., Jeffries, N. O. et al. (1999). "Brain development during childhood and adolescence: a longitudinal MRI study". *Nature Neuroscience* 2(10): 861–863. DOI: 10.1038/13158.

Gill, D., and Prowse, V. (2016). "Cognitive Ability, Character Skills, and Learning to Play Equilibrium: A Level-k Analysis". *Journal of Political Economy* 124(6): 1619–1676. DOI: 10.1086/688849.

Glover, D., Pallais, A., and Pariente, W. (2017). "Discrimination as a Self-Fulfilling Prophecy: Evidence from French Grocery Stores". *Quarterly Journal of Economics* 132(3): 1219–1260. DOI: 10.1093/qje/qjx006.

Heckman, J. J. (2008). "Schools, Skills, and synapses". *Economic Inquiry* 46(3): 289–324. DOI: 10.1111/j.1465-7295.2008.00163.x.

Hvidberg, K. B., Kreiner, C. T., and Stantcheva, S. (2023). "Social Positions and Fairness Views on Inequality". *Review of Economic Studies* 90(6): 3083–3118. DOI: 10.1093/restud/rdad019.

Jakiela, P., Miguel, E., and Te Velde, V. L. (2015). "You've earned it: estimating the impact of human capital on social preferences". *Experimental Economics* 18(3): 385–407. DOI: 10.1007/s10683-014-9409-9.

Johnson, E. J., and Payne, J. W. (1985). "Effort and Accuracy in Choice". *Management Science* 31(4): 395–414. DOI: 10.1287/mnsc.31.4.395.

Jones, M. T. (2014). "Strategic complexity and cooperation: An experimental study". *Journal of Economic Behavior & Organization* 106: 352–366. DOI: 10.1016/j.jebo.2014.07.005.

Kautz, T., Heckman, J. J., Diris, R., ter Weel, B., and Borghans, L. (2014). "Fostering and Measuring Skills: Improving Cognitive and Non-Cognitive Skills to Promote Lifetime Success". DOI: 10.3386/w20749, NBER Working Paper No. 20749.

Keating, D. P. (2004). "Cognitive and Brain Development". In *Handbook of Adolescent Psychology*, edited by Lerner, R., and Steinberg, L.: 45–84, Hoboken (NJ), US: Wiley.

Konow, J. (2000). "Fair Shares: Accountability and Cognitive Dissonance in Allocation Decisions". *American Economic Review* 90(4): 1072–1091. DOI: 10.1257/aer.90.4.1072.

Kosse, F., Deckers, T., Pinger, P., Schildberg-Hörisch, H., and Falk, A. (2020). "The Formation of Prosociality: Causal Evidence on the Role of Social Environment". *Journal of Political Economy* 128(2): 434–467. DOI: 10.1086/704386.

Lambrecht, M., Proto, E., Rustichini, A., and Sofianos, A. (2024). "Intelligence Disclosure and Cooperation in Repeated Interactions". *American Economic Journal: Microeconomics* 16(3): 199–231. DOI: 10.1257/mic.20220245.

Lucchetti, A. H., and Cajueiro, D. O. (2025). "Language as Data: A Survey of Natural Language Processing for Economics and Finance". *Journal of Economic Surveys*. DOI: 10.1111/joes.70014.

Ludwig, J., Mullainathan, S., and Rambachan, A. (2025). "Large Language Models: An Applied Econometric Framework". DOI: 10.3386/w33344, NBER Working Paper No. 33344.

Martínez-Marquina, A., Niederle, M., and Vespa, E. (2019). "Failures in Contingent Reasoning: The Role of Uncertainty". *American Economic Review* 109(10): 3437–3474. DOI: 10.1257/aer.20171764.

Martinsson, P., Nordblom, K., Rützler, D., and Sutter, M. (2011). "Social preferences during childhood and the role of gender and age —An experiment in Austria and Sweden". *Economics Letters* 110(3): 248–251. DOI: 10.1016/j.econlet.2010.11.028.

Newell, A., and Simon, H. A. (1972). *Human Problem Solving* Volume 104. Englewood Cliffs, NJ: Prentice Hall.

Neyman, A. (1985). "Bounded complexity justifies cooperation in the finitely repeated prisoners' dilemma". *Economics Letters* 19(3): 227–229. DOI: 10.1016/0165-1765(85)90026-6.

Oprea, R. (2020). "What Makes a Rule Complex?". *American Economic Review* 110(12): 3913–3951. DOI: 10.1257/aer.20191717.

Oprea, R. (2024). "Decisions under Risk Are Decisions under Complexity". *American Economic Review* 114(12): 3789–3811. DOI: 10.1257/aer.20221227.

Oprea, R. (2025). "Complexity and Its Measurements". Manuscripter prepared for the Handbook of Experimental Methods in the Social Sciences.

Parsons, C. A., Sulaeman, J., Yates, M. C., and Hamermesh, D. S. (2011). "Strike Three: Discrimination, Incentives, and Evaluation". *American Economic Review* 101(4): 1410–35. DOI: 10.1257/aer.101.4.1410.

Paus, T. (2005). "Mapping brain maturation and cognitive development during adolescence". *Trends in Cognitive Sciences* 9(2): 60–68. DOI: 10.1016/j.tics.2004.12.008.

Payne, J. W., Bettman, J. R., and Johnson, E. J. (1993). *The Adaptive Decision Maker*, Cambridge University Press.

Preuss, M., Reyes, G., Somerville, J., and Wu, J. (2025). "Inequality of Opportunity and Income Redistribution". DOI: `10.48550/arXiv.2209.00534`.

Proto, E., Rustichini, A., and Sofianos, A. (2019). "Intelligence, Personality, and Gains from Cooperation in Repeated Interactions". *Journal of Political Economy* 127(3): 1351–1390. DOI: `10.1086/701355`.

Proto, E., Rustichini, A., and Sofianos, A. (2022). "Intelligence, Errors, and Cooperation in Repeated Interactions". *Review of Economic Studies* 89(5): 2723–2767. DOI: `10.1093/restud/rdab095`.

Puri, I. (2025). "Simplicity and Risk". *Journal of Finance* 80(2): 1029–1080. DOI: `10.1111/jofi.13417`.

Raven, J. C. (1936). "Mental tests used in genetic studies: The performance of related individuals on tests mainly educative and mainly reproductive". MSc thesis, University of London.

Raven, J. (2000). "The Raven's Progressive Matrices: Change and Stability over Culture and Time". *Cognitive Psychology* 41(1): 1–48. DOI: `10.1006/cogp.1999.0735`.

Rawls, J. (1971). *A Theory of Justice*, Cambridge, MA: Harvard University Press.

Reverberi, C., Pischedda, D., Mantovani, M., Haynes, J.-D., and Rustichini, A. (2022). "Strategic complexity and cognitive skills affect brain response in interactive decision-making". *Scientific Reports* 12(1). DOI: `10.1038/s41598-022-17951-0`.

Roemer, J. E. (1993). "A Pragmatic Theory of Responsibility for the Egalitarian Planner". *Philosophy & Public Affairs* 22(2): 146–166.

Roemer, J. E. (1998). *Equality of Opportunity*, Cambridge, MA: Harvard University Press.

Rubinstein, A. (1986). "Finite automata play the repeated prisoner's dilemma". *Journal of Economic Theory* 39(1): 83–96. DOI: `10.1016/0022-0531(86)90021-9`.

Schunk, D., and Zipperle, I. (2023). "Fairness and inequality acceptance in children and adolescents: A survey on behaviors in economic experiments". *Journal of Economic Surveys* 37(5): 1715–1742. DOI: `10.1111/joes.12553`.

Selten, R. (1967). "Die Strategiemethode zur Erforschung des eingeschränkt rationalen Verhaltens im Rahmen eines Oligopolexperiments". In *Beiträge zur experimentellen Wirtschaftsforschung*, edited by Sauermann, H.: 136–168, Tübingen, NL: Mohr.

Simon, H. A. (1955). "A Behavioral Model of Rational Choice". *Quarterly Journal of Economics* 69(1): 99. DOI: `10.2307/1884852`.

Stantcheva, S. (2021). "Understanding Tax Policy: How do People Reason?". *Quarterly Journal of Economics* 136(4): 2309–2369. DOI: 10.1093/qje/qjab033.

Steinberg, L. (2005). "Cognitive and affective development in adolescence". *Trends in Cognitive Sciences* 9(2): 69–74. DOI: 10.1016/j.tics.2004.12.005.

Sutter, M., Feri, F., Glätzle-Rützler, D., Kocher, M. G., Martinsson, P., and Nordblom, K. (2018). "Social preferences in childhood and adolescence. A large-scale experiment to estimate primary and secondary motivations". *Journal of Economic Behavior & Organization* 146: 16–30. DOI: 10.1016/j.jebo.2017.12.007.

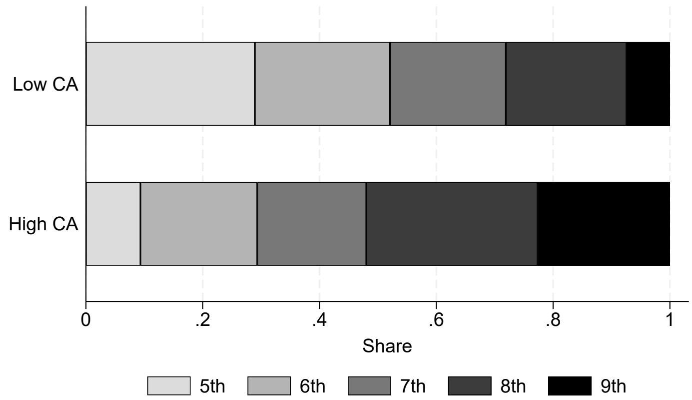
Temkin, L. (1993). *Inequality*, Oxford: Oxford University Press.

Tversky, A., and Kahneman, D. (1974). "Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty.". *Science* 185(4157): 1124–1131. DOI: 10.1126/science.185.4157.1124.

Varian, H. R. (2014). "Big Data: New Tricks for Econometrics". *Journal of Economic Perspectives* 28(2): 3–28. DOI: 10.1257/jep.28.2.3.

A Additional results

Figure A.1: Grade Distribution within Cognitive Ability Groups



Notes: This figure plots the distribution of participants in each cognitive ability group. Cognitive ability groups are split by the median score in the Raven's SPM test (8 out of 12). Students grade is distinguished. Grades colores in yellow comprise the younger age group. Grades colored in green comprise the older age group. For more details, see Table A.1.

Table A.1: Cognitive Ability and Age

	Cognitive Ability	
	Mean score	Share High
	(1)	(2)
Panel A. Age		
Ages 10-12	.583	.293
Ages 13-15	.700	.534
Panel B. Grade		
Year 5	.532	.167
Year 6	.605	.349
Year 7	.616	.368
Year 8	.688	.468
Year 9	.721	.654

Notes: This table reports cognitive ability measurements by school grade. Column (1) shows mean scores out of 100%. Column (2) shows the share of students above school median score.

Table A.2: Heterogeneities by Age

	Egalitarian				Libertarian			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
8th/9th	-.124***				-.004			
	(.044)				(.046)			
High CA		-.109**	-.098	-.067		-.022	.049	-.123
		(.046)	(.072)	(.054)		(.046)	(.068)	(.077)
Sample	All	All	5th/7th	8th/9th	All	All	5th/7th	8th/9th
Dep. var. mean	.131	.131	.177	.054	.111	.111	.113	.108
Effect magn.	-95%	-83%	-56%	-124%	-3%	-20%	43%	-114
Observations	198	196	123	73	198	196	123	73
R^2	.034	.028	.021	.021	.007	.009	.016	.040

	Fact. Merit.				Counter. Merit.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
8th/9th	-.040				.168**			
	(.073)				(.066)			
High CA		-.013	.015	-.032		.144**	.034	.222**
		(.074)	(.100)	(.121)		(.065)	(.078)	(.110)
Sample	All	All	5th/7th	8th/9th	All	All	5th/7th	8th/9th
Dep. var. mean	.510	.510	.524	.486	.247	.247	.185	.351
Effect magn.	-8%	-3%	3%	-7%	68%	58%	19%	63%
Observations	198	196	123	73	198	196	123	73
R^2	.017	.014	.017	.010	.051	.040	.029	.058

Notes: This table reports the coefficients of dummies on age and cognitive ability groups on preferred distribution criteria. The independent variables are computed as dummy variables. Age groups are formed based on current school grade: valued 1 for students from 8th to 9th grade, and 0 otherwise. Cognitive ability groups are formed based on cognitive ability measurement: valued 1 for students scoring above the median (8 out of 12), and 0 otherwise. The dependent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for sex. Robust standard errors are reported in parentheses for the remaining columns. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Heterogeneities by Gender

(a) Boys

		Age			Cognitive Ability		
	Total	5th/7th	8th/9th	Diff.	Low	High	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Egalitarians	.116	.155	.049	-.106*	.132	.083	-.048
				(.055)			(.061)
Libertarians	.134	.141	.122	-.019	.145	.111	-.034
				(.066)			(.067)
Fact. Merit.	.455	.465	.439	-.026	.474	.417	-.057
				(.098)			(.101)
Counter. Merit.	.295	.239	.390	.151	.250	.389	.139
				(.092)			(.096)

(b) Girls

		Age			Cognitive Ability		
	Total	5th/7th	8th/9th	Diff.	Low	High	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Egalitarians	.151	.208	.061	-.147**	.222	.073	-.149*
				(.070)			(.075)
Libertarians	.081	.075	.091	.015	.089	.073	-.016
				(.063)			(.059)
Fact. Merit.	.581	.604	.545	-.058	.578	.585	.008
				(.111)			(.108)
Counter. Merit.	.186	.113	.303	.190**	.111	.268	.157*
				(.092)			(.085)

Notes: These tables report stated preferences shares. Panel (a) restricts to boys. Panel (b) restricts to girls. Column (1) show refers to the whole sample. Columns (2) to (4) distinguishes by age group. Groups are formed based on current school grade. The first group comprises students from 5th to 7th grade. Ages in those grades range from 10 to 13 years old. The second group comprises students from 8th to 9th grade. Ages in those grades range from 13 to 15 years old. Columns (2) and (3) report the share of each fairness view in each group. Column (4) reports the difference between the two groups. Columns (5) to (7) distinguishes by cognitive ability. Groups are formed based on the median of the cognitive ability measurement. The first group (low) has scores on the median or below. The second group (high) has scores above the median. Columns (5) and (6) report the share of each fairness view in each group. Column (7) reports the difference between the two groups. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Participant's Comprehension

		Age			Cognitive Ability		
	Total	5th/7th	8th/9th	Diff.	Low	High	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Egalitarians	.099	.127	.050	-.077*	.131	.048	-.083*
				(.044)			(.044)
Libertarians	.111	.118	.100	-.018	.131	.081	-.051
				(.050)			(.049)
Fact. Merit.	.531	.549	.500	-.049	.535	.532	-.003
				(.082)			(.081)
Counter. Merit.	.259	.206	.350	.144*	.202	.339	.137*
				(.074)			(.073)

Notes: This table reports stated preferences shares. **Sample excludes participants who failed to understand part of the instructions.** Column (1) show refers to the whole sample. Columns (2) to (4) distinguishes by age group. Groups are formed based on current school grade. The first group comprises students from 5th to 7th grade. Ages in those grades range from 10 to 13 years old. The second group comprises students from 8th to 9th grade. Ages in those grades range from 13 to 15 years old. Columns (2) and (3) report the share of each fairness view in each group. Column (4) reports the difference between the two groups. Columns (5) to (7) distinguishes by cognitive ability. Groups are formed based on the median of the cognitive ability measurement. The first group (low) has scores on the median or below. The second group (high) has scores above the median. Columns (5) and (6) report the share of each fairness view in each group. Column (7) reports the difference between the two groups. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Alternative Cutoffs

(a) Age

	6th grade			8th grade		
	5th/6th	7th/9th	Diff.	5th/8th	9th	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)
Egalitarians	.244	.045	-.200***	.140	.077	-.063
			(.051)			(.059)
Libertarians	.116	.107	-.009	.122	.038	-.084*
			(.045)			(.045)
Fact. Merit.	.465	.545	.080	.517	.462	-.056
			(.072)			(.105)
Counter. Merit.	.174	.304	.129**	.221	.423	.202**
			(.060)			(.102)

(b) Cognitive Ability

	Score = 7			Score = 9		
	Low	High	Diff.	Low	High	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)
Egalitarians	.182	.091	-.091*	.147	.071	-.076
			(.050)			(.049)
Libertarians	.136	.091	-.045	.122	.071	-.050
			(.046)			(.048)
Fact. Merit.	.477	.536	.059	.526	.452	-.073
			(.072)			(.087)
Counter. Merit.	.205	.282	.077	.205	.405	.200**
			(.061)			(.083)

Notes: These tables report stated preferences shares, distinguishing by age and cognitive ability groups. Panel (a) distinguishes by age groups. Age groups are formed based on current school grade. Columns (1) to (3) split groups by 6th grade. The first group comprises students from 5th to 6th grade. Ages in those grades range from 10 to 12 years old. The second group comprises students from 7th to 9th grade. Ages in those grades range from 12 to 15 years old. Columns (4) to (6) split groups by 8th grade. The first group comprises students from 5th to 8th grade. Ages in those grades range from 10 to 14 years old. The second group comprises students 9th grade. Ages in those grades range from 14 to 15 years old. Panel (b) distinguishes by cognitive ability. Columns (1) to (3) split groups starting from a test score of 7. The first group (low) has scores of 7 or below. The second group (high) has scores above 7. Columns (4) to (6) split groups starting from a test score of 9. The first group (low) has scores of 9 or below. The second group (high) has scores above 9. For both panels, columns (1) and (2) report the share of each fairness view in each group. Column (3) reports the difference between the two groups. Columns (4) and (5) report the share of each fairness view in each group. Column (6) reports the difference between the two groups. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Experimental Manipulations

	Total	Low CA	High CA	Diff.	CA coef.
	(1)	(2)	(3)	(4)	(5)
Panel A. Main fairness views					
Egalitarian	.111	.152	.040	-.112*	-.062
				(.067)	(.042)
Meritocrat	.750	.696	.840	.144	.085
				(.101)	(.056)
Libertarian	.139	.152	.120	-.032	-.024
				(.085)	(.048)
Panel B. Within Meritocrats					
Actual choice Meritocrat	.528	.565	.480	-.085	.005
				(.126)	(.060)
Comparable choice Meritocrat	.222	.130	.360	.230**	.081*
				(.110)	(.045)

Notes: This table reports fairness view shares. **Samples excludes participants in `T1` and in `T2`.** Sample size is 72. Columns (1) refers to the whole sample. Columns (2) to (4) distinguishes by cognitive ability. Groups are formed based on the median of the cognitive ability measurement. The first group (low) has scores below the median. The second group (high) has scores above the median. Columns (2) and (3) report the share of each fairness view in each group. Columns (4) reports the difference between the two groups. Columns (5) reports estimates of cognitive ability on fairness views. The dependent variables are valued 1 for each stated fairness view, and 0 otherwise. The independent variable is the standardized cognitive ability test score. Each row reports estimates from a linear model. Robust standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.7: Proxies for Fairness Views Complexity

	Implementation error	Compared with Merit.	
		w/o covs.	with covs.
	(1)	(2)	(3)
Panel A. Main fairness views			
Egalitarian	.086	-.038***	-.052***
		(.012)	(.012)
Meritocrat	.124		
Libertarian	.143	.019	.019
		(.013)	(.013)
Panel B. Within Meritocrats			
Actual choice	.110	-.043***	-.046***
		(.009)	(.009)
Comparable choice	.152	.043***	.046***
		(.009)	(.009)

Notes: This table reports behavior by fairness view. Columns (1) shows mean implementation error in absolute terms. Columns (2) and (3) report estimates of each fairness views on implementation error, using Meritocrats as the reference group. The dependent variable is implementation error. The independent variables are valued 1 for each stated fairness view, and 0 for Meritocrats. Each cell reports estimates from a linear model Estimates in column (2) are from simple linear models, and estimates in column (3) account for age and sex variations. Robust standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

B Spectator phase

B.1 Experimental procedures

The spectator phase consists of two stages: distribution decisions with incentivized belief elicitations, and surveys. Participants are randomly assigned to different treatment conditions in a between-subject setting. Treatments differ on the first stage and are equal in the second stage. Figure 1 in the main text details the spectator phase flow.

First stage. We start by laying out the workers phase setting. We explain that real people were hired to work in a number of effort tasks, that commitments were made for a low and high piece-rate value, that the piece-rate value was randomly assigned, and that workers had to honor their commitment. Throughout the spectator phase we use visual aid, to make the information easy to understand. The piece-rate assignment is explained through flipping a red and blue coin. Those workers who get the red side of the coin are assigned the low piece-rate, while those who get the blue side are assigned the high piece-rate. The low piece-rate worker is labeled as 'Worker A' and is colored in red. The high piece-rate worker is labeled as 'Worker B' and is colored in blue. We explain that workers earn points, which can be later traded for money. The point-to-money conversion rate is $0.06 = 1 points, implying that the low piece-rate is 1 point and the high piece-rate is 10 points. Participants are not aware of the conversion rate.

Then, we explain the pair formation, noting that each pair comprises one red worker (receiving the low piece-rate) and one blue worker (receiving the high piece-rate). We inform participants that they will decide how to distribute points within pairs, emphasizing that there is no correct or incorrect answer. We explain participants that they will be presented five pairs, one of which is real and that their decisions could be implemented in real life. We announce that 1 in 10 spectators will make a decision with real consequences. Spectators are aware that workers expect a third-party may influence their payment, but cannot know their identity.

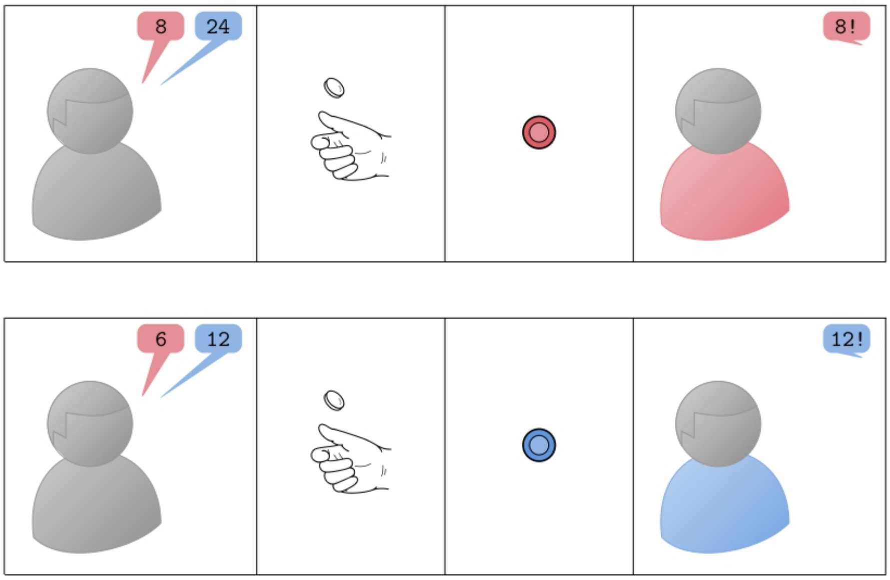
Before starting with the distributions and belief elicitations we run a comprehension test. There is no limited time or opportunities to answer. Participants are allowed to ask questions to the assisting teachers in the room. Teachers were explained the setting in the weekly coordination meeting, but are unaware of the experiment's research questions. Participants can only start with the distributions and belief elicitations after all questions in the comprehension test are correctly answered. Depending on the treatment, participants are first presented with the distribution decisions or with belief elicitations.

For treatment conditions `T0` and `T1`, participants are first presented with the distribution decisions. Participants decide on the point distribution within pairs in 5 scenarios. After the 5 scenarios, participants respond a post-decision survey. Following, spectators are offered the possibility of gaining additional information to remake decisions. Finally, participants are presented with the belief elicitations.

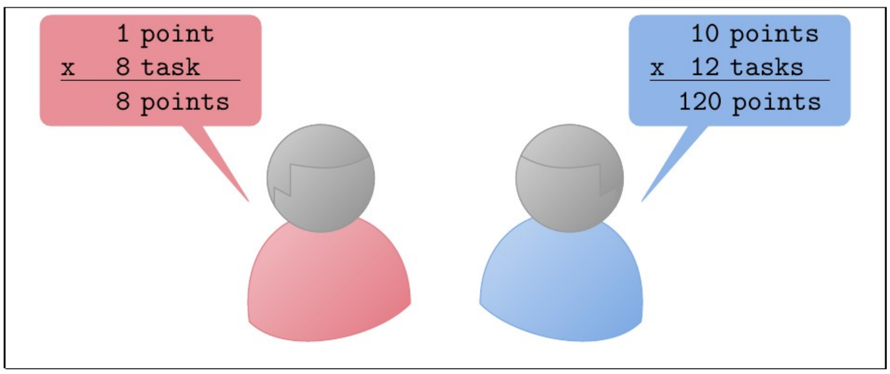
For treatment condition `T2`, participants are presented first with the belief elicitations. Participants guess one worker's task commitment for the non-assigned piece-rate in one scenario. Then, participants are

Figure C.1: Figures used to explain the worker phase

(a) Piece-rate assignment



(b) Pair formation



Notes: These figures were shown to explain the worker phase. Figures (a) show the task commitment and random piece-rate assignment. We use colors to differentiate commitments and assignments to different piece-rates. Red is used for the low piece-rate and blue for the high piece-rate. We use a coin flip to explain the random assignment. Figure (b) shows team formation.

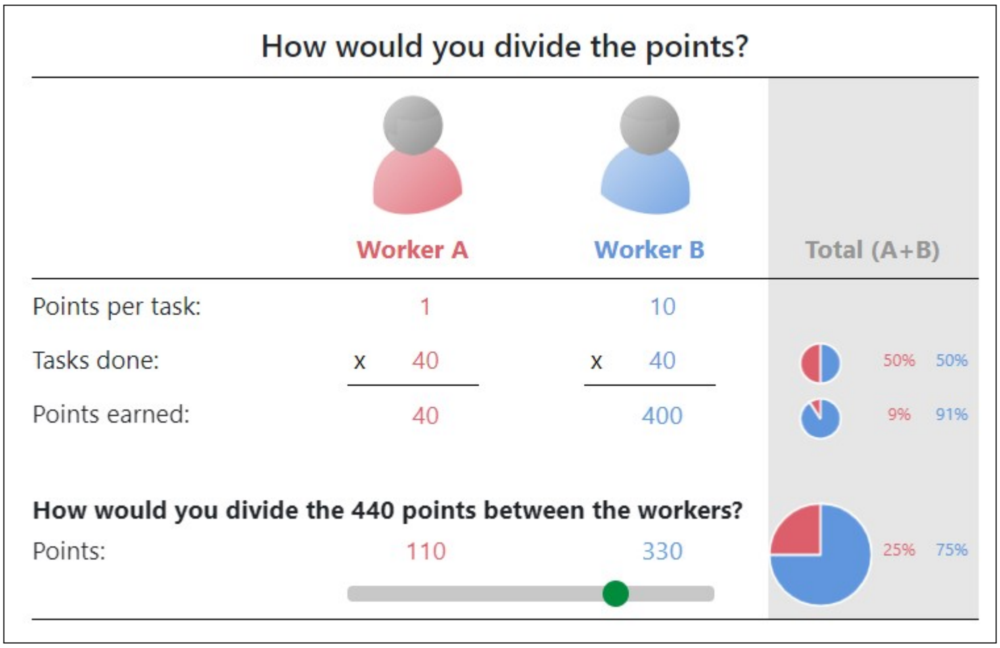
presented with the distribution decision for the same scenario. The distribution decision is made as in treatment conditions `T0` and `T1`. For each scenario participants complete the belief elicitation and the distribution decision. After the 5 scenarios, participants respond a post-decision survey. Finally, spectators are offered the possibility of gaining additional information to remake decisions.

Distribution decisions. See Figure C.2 for a screenshot of the distribution decision. Participants decide on the point distribution within pairs for five scenarios. Decisions are made with a slider and aided by a dynamic graph plotting the share assigned to each worker. There is no time limit, but a pop-up window appears 1 minute after the scenario is presented.

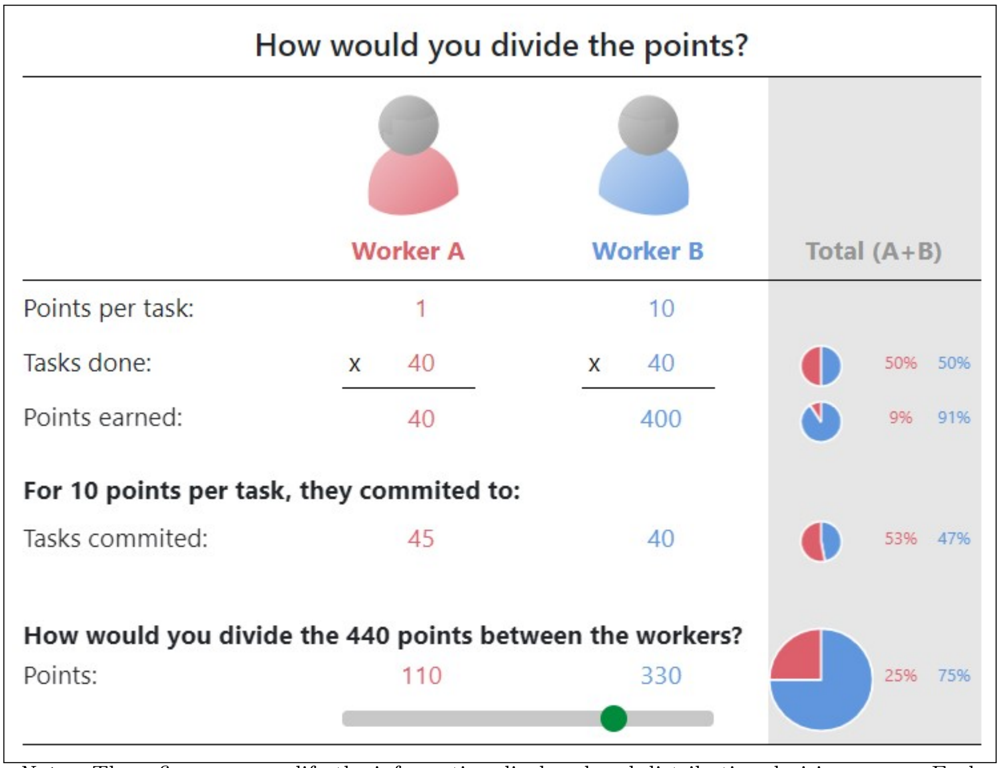
Post-decision survey. After deciding for the five scenarios, participants are randomly presented one decision and asked to justify it. There is a minimum character limit of 100 characters. In the next screen,

Figure C.2: Distribution decision screen, by treatment conditions

(a) `T0/T2` treatments



(b) `T1` treatment



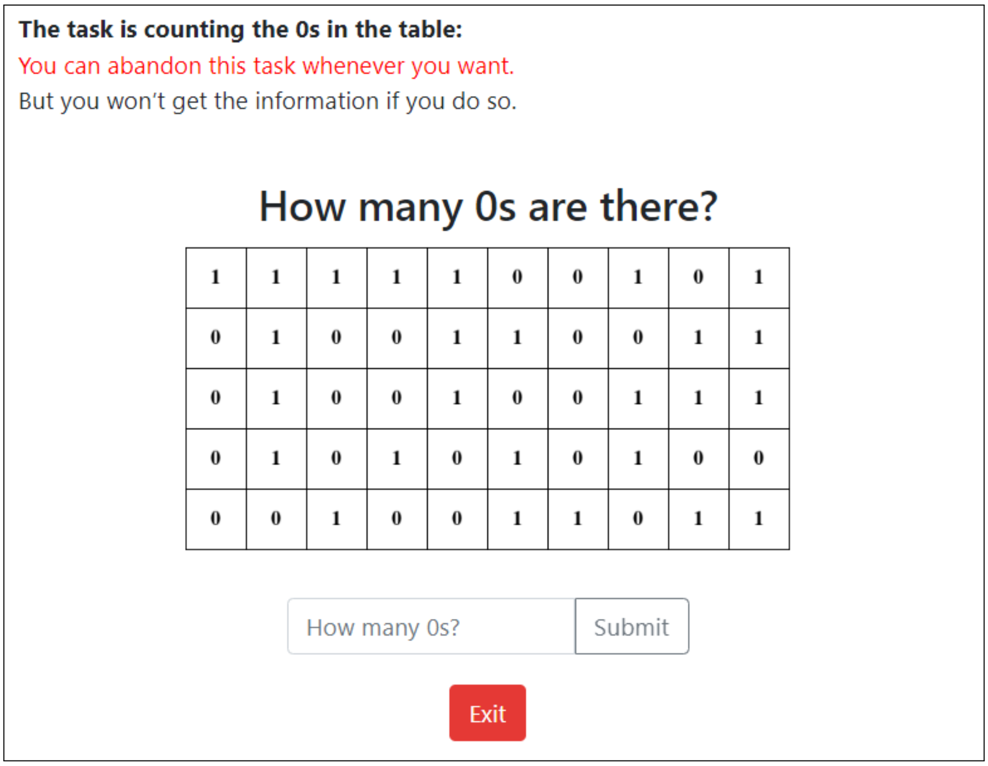
Notes: These figures exemplify the information displayed and distribution decision screen. Each figure shows a pair of workers. In the `T0/T2` treatments I provide information about piece-rate payment, tasks completed, and initial earnings for each worker. In the `T1` treatment I additionally disclose the task commitment for a same piece-rate payment (randomly selected for each pair). I also display shares for tasks and earnings (automatically computed). Participants can modify the allocation by moving the slider. A dynamic graph updates with the spectator's decision.

participants answer a non-incentivized survey. We ask which is their preferred distribution criteria for distributing within pairs. We present a close list, with each statement adhering to (i) egalitarianism, (ii) libertarianism, (iii) actual choice meritocracy, and (iv) comparable choice meritocracy. Responses are presented in random order. We also ask about the worker they would prefer to be, the identity of the real team, and the degree of understanding of the task.

Gaining additional information. After the post-decision survey, spectators are offered the possibility of gaining additional information to remake decisions. Offered information is on worker's effort commitment under equal opportunities. To access such information, spectators need to complete a counting-zeros task (Abeler et al., 2011). Spectators are able to take or not the opportunity.

The task consists on counting zeros in a matrix. We present a square matrix composed of 1s and 0s (see Figure C.3). The task is to enter the total number of 0s in the matrix. There is no limited time or opportunities to answer. We ask participants to complete one matrix to acquire information. Participants are able to withdraw from the task at any time, loosing access to the additional information.

Figure C.3: Counting-zeros task example

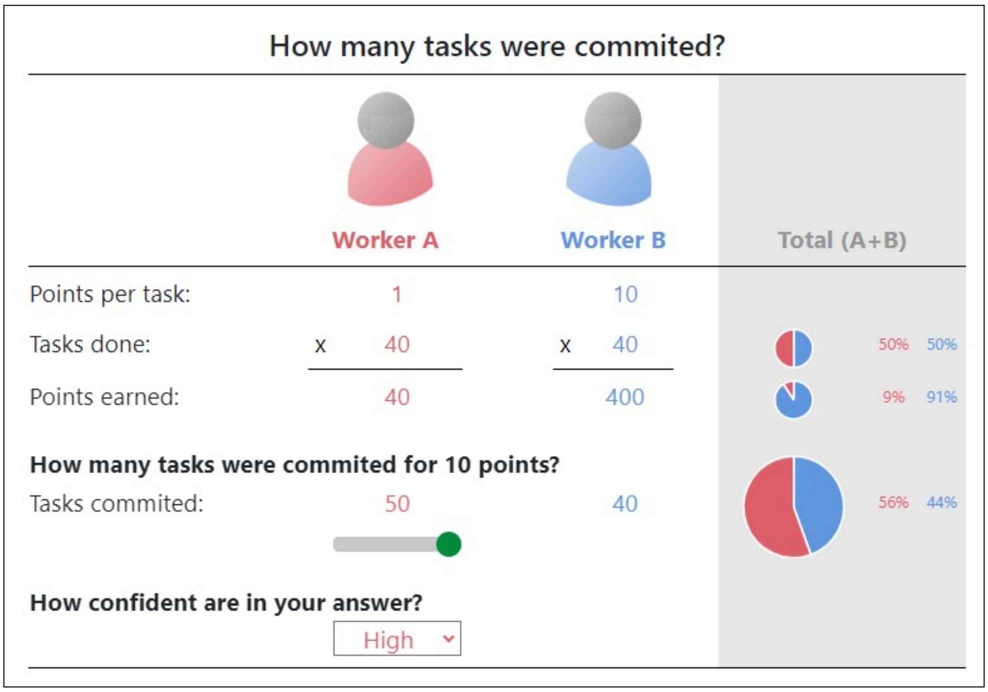


Notes: This screenshot exemplifies the counting-zeros task. The table displayed shows a random sequence of 1s and 0s. The participant is shown the table and asked how many 0s are there in the table. The correct answer for this table is 24.

Participants who successfully complete the task are presented with the information and asked to remake their decision for the scenario they guessed as the real one. The remake decision is made at the end of the first stage. Except for the provided information, the decision is made equally to previous decisions.

Belief elicitation. See Figure C.4 for a screenshot of the belief elicitation. Participants guess one worker's task commitment for the non-assigned piece-rate. The worker is randomly selected in each scenario. Guesses are made with a slider and aided by a dynamic graph. There is no time limit, but a pop-up window appears 1 minute after the scenario is presented.

Figure C.4: Belief Elicitation



Notes: This figure exemplifies the belief elicitation screen, translating from the original screen with text in Spanish. Participants are randomly shown task commitments for a reference piece-rate, and asked to guess for the worker non-assigned the reference piece-rate. Participants can modify their inference by moving the slider. All treatment arms feature belief elicitation.

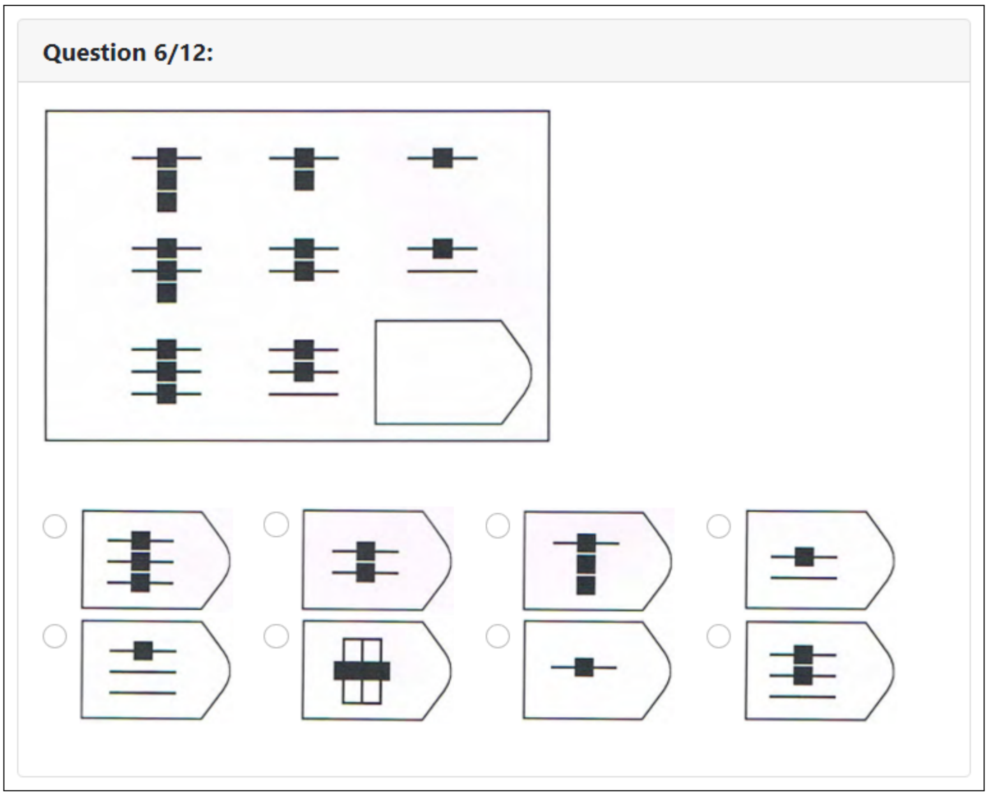
Second stage. We run two surveys: one is incentivized and the other one is non-incentivized.

Incentivized survey. We include the twelve items from Raven's Standard Progressive Matrices (SPM) test (Raven, 1936, 2000). Figure C.5 exemplifies it. Each item is a 3x3 matrix with a missing cell in the bottom right corner. Participants are asked to select the missing cell out of eight choices provided. Participants receive the test instructions before it begins. We require participants to answer a small set of comprehension questions. These refer to time allocation, number of correct options per item and an illustrative item (previously used in the instructions). The test only begins after all comprehension questions are correctly answered.

The test is presented in increasing difficulty order. Participants are able to navigate back and forth throughout the test to review and modify their answers. The test lasts up to 6 minutes. All unanswered items are considered incorrect. We incentivize performance by rewarding if correct four randomly picked items.

Non-incentivized survey. We ask participant a small set of questions. These questions concern age, gender, educational background, neighborhood of residence, household's size and assets, and canteen consumption. There is no time limit to respond the survey.

Figure C.5: Raven's Standard Progressive Matrices test example



Notes: This screenshot exemplifies Raven's Standard Progressive Matrices (SPM) test. The upper image shows a 3x3 matrix with a missing cell. The task is to guess the image that corresponds to the missing cell. Only one out of the eight possible choices depicted below the matrix is correct. This is item number 6 of the SPM test. The correct answer is choice 5.

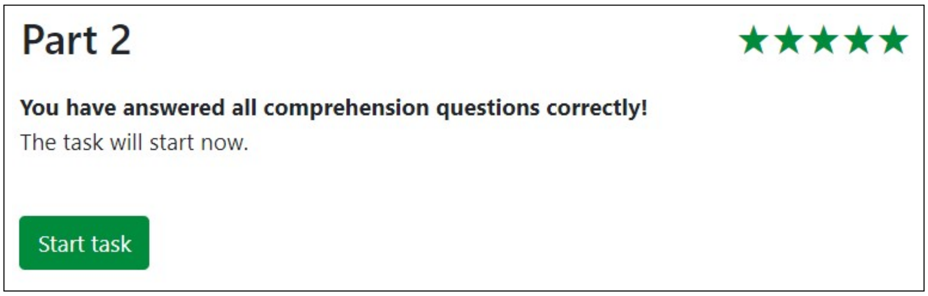
After the surveys are completed, participants are thanked and dismissed.

Reward details. At the beginning of the experiment, we inform participants that they will all receive rewards. We present three prize baskets, which are on display to see. Each prize basket has escalating prizes. We explain that the basket each will obtain depends on how much '*stars*' each accumulates throughout the session.

Participants accumulate '*stars*' on several screens of the experiment. The distribution decisions and non-incentivized survey yield a fixed number of '*stars*' for completion. The belief elicitation and the incentivized survey yield '*stars*' depending on response accuracy. The instructions preceding each part of the experiment clearly state how '*stars*' are awarded. The total number of '*stars*' is displayed in the top right corner in each screen of the experiment.

At the end of the experiment, participants are informed how many '*stars*' they earned and which prize basket they obtain. Rewards are delivered in sealed bags anonymously, based on computer's number.

Figure C.6: Screenshots displaying accumulated stars



Notes: This screenshot exemplifies how stars are shown in each screen. Stars are colored in green and always displayed in the top right corner. After a star is earned, a screen pops-up displaying the number of stars earned during 5 seconds.

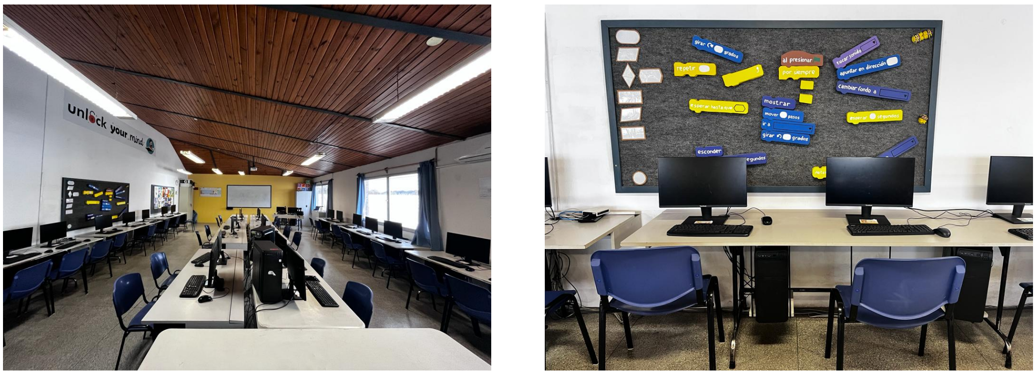
B.2 Implementation

We recruited 198 students from a private school in Montevideo in September 2023. Participation was available for all students from 5th grade to 9th grade.

The data recollection was run across four weekdays, in the school's computer lab during regular computing hours. The logistics were arranged in coordination with the school's principal board and the computing team coordination. We use the infrastructure of the school's computer lab, comprising 30 computers. With every class having under 28 students enrolled, we had no problem fitting all participants in the lab.

Figure C.7: Computer lab used

(a) Room **(b) Computer setup**



Notes: These figures show the school's computer lab, where all sessions took place. Figure (a) shows the room from the entrance. Figure (b) shows the computer setups.

We requested approval by the parents of involved students. The school delivered a consent form containing information on the project, with an explicit endorsement. No specific details on the tasks or aim of the research was communicated. Children were also instructed that their participation was voluntary.

We offered participants prize baskets containing canteen products. All participants received a reward worth 75 UYP ($\sim$ 2.00 USD) for participation and could earn products worth up to 265 UYP ($\sim$ 7.00 USD). We set the expected time to complete the study to 30 minutes, below the average computing class duration. The study was fully conducted in Spanish.

B.3 Results

The study was completed in 10 sessions throughout four days. Each session consisted of an entire group. Each grade consists of two groups. Sessions were run during computing class and lasted its whole duration.

All parents and students agreed to participate in the study. Attendance to the school was almost complete (see Table C.1). All attending students during computing class participated in the activity. Average value of the prize basket reward was 113 Uruguayan Pesos ($\sim$ 3.00 USD).

Table C.1: School attendance

Grade	Group	Absent (1)	Attendance (2)
5th	East	4	.826
5th	West	2	.920
6th	North	3	.875
6th	South	2	.920
7th	North	2	.905
7th	South	4	.826
8th	North	0	1.000
8th	South	2	.920
9th	North	0	1.000
9th	South	1	.929
5th-9th	**All**	**20**	**.908**

Notes: This table reports school attendance the day each group participated in the study. There are two groups per grade, labeled by the cardinal direction of the classroom. Column (1) reports number of absentees in each group. Column (2) reports the attendance rate for each group.

Table C.2 compares characteristics of our sample with Montevidean population based on data from the 2022 Uruguayan Household Survey. In short, spectators come from households with higher income per capita than the population. The sample is part of a reduced group of households with low material limitations.

Table C.2: Sample characteristics

	Spectators	Population	Difference
	(1)	(2)	(3)
Panel A. Individuals			
Male	.563	.515	.048
			(.037)
All education in school	.753	-	-
New to school	.056	-	-
Daily canteen expenditure	.87	-	-
Panel B. Households			
Cars: 2+	.929	.092	.837***
			(.019)
Rooms: 5+	.697	.233	.464***
			(.034)
Income per capita: $1000+	.970	.270	.700***
			(.016)
Under the poverty line	.000	.195	-.194***
			(.009)

Notes: This table reports statistics for the spectator sample and the population. The population sample covers all individuals in the same age bracket living in the same city. Panel A refers to individual characteristics. Panel B refers to household characteristics. Rows 5 to 7 show household shares. Row 5 refers to total number of cars in the individual's home. Row 6 refers to total number of rooms (excluding bathrooms and kitchen) in the individual's home. Row 7 and 8 include non-parametrics estimates for the spectator sample based in data from the 2022 Uruguayan Household Survey. All income are expressed in 2023 United States Dollars (USD). Columns (1) and (2) show mean shares. Column (3) shows differences between spectators and general population. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

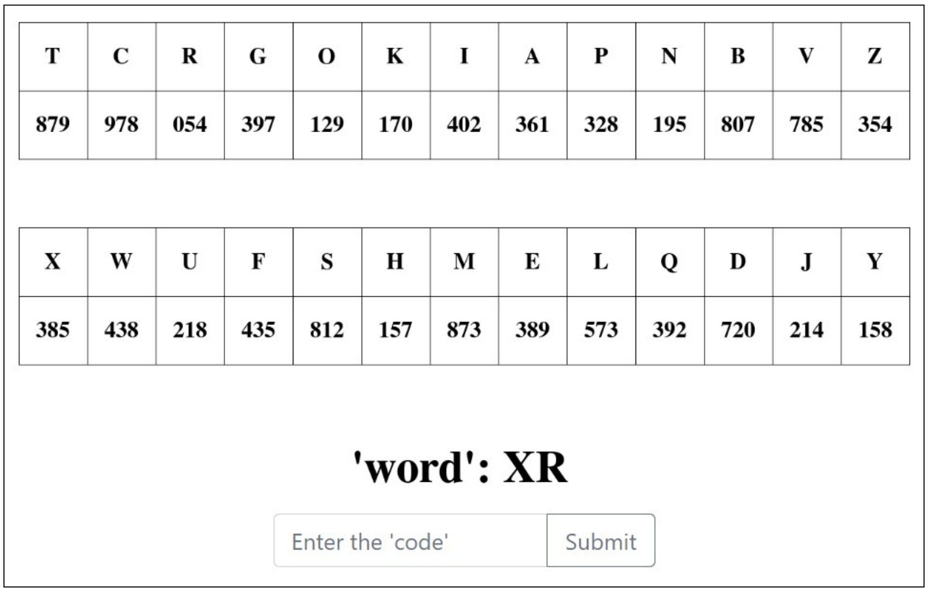
C Worker phase

C.1 Experimental procedures

The worker phase consists of the commitment and completion of letter-to-number encryption tasks. Figure D.1 exemplifies one task. Participants are explained how the encryption works and are asked to complete 3 encryptions, as trial. Afterwards, participants are asked to commit to a number of encryptions for each of two piece-rate payments: low (£0.05, $\sim$ \$0.06), or high (£0.50, $\sim$ \$0.60). Each participant is randomly assigned to one of the two piece-rate payments and has to honor their commitment for that piece-rate.

Task presentation. We present a '*word*', formed by letters. Every letter has a 3-digit number assigned, displayed in a separate encryption table. Worker's task is to submit the '*code*' assigned to the '*word*'. Workers can only proceed to the next '*word*' if the encryption is done correctly. There is no limited time or opportunities to answer. Once the correct '*code*' is supplied, the workers can proceed to a new '*word*' and encryption table.

Figure D.1: Letter-to-number encryption task example



T	C	R	G	O	K	I	A	P	N	B	V	Z
879	978	054	397	129	170	402	361	328	195	807	785	354

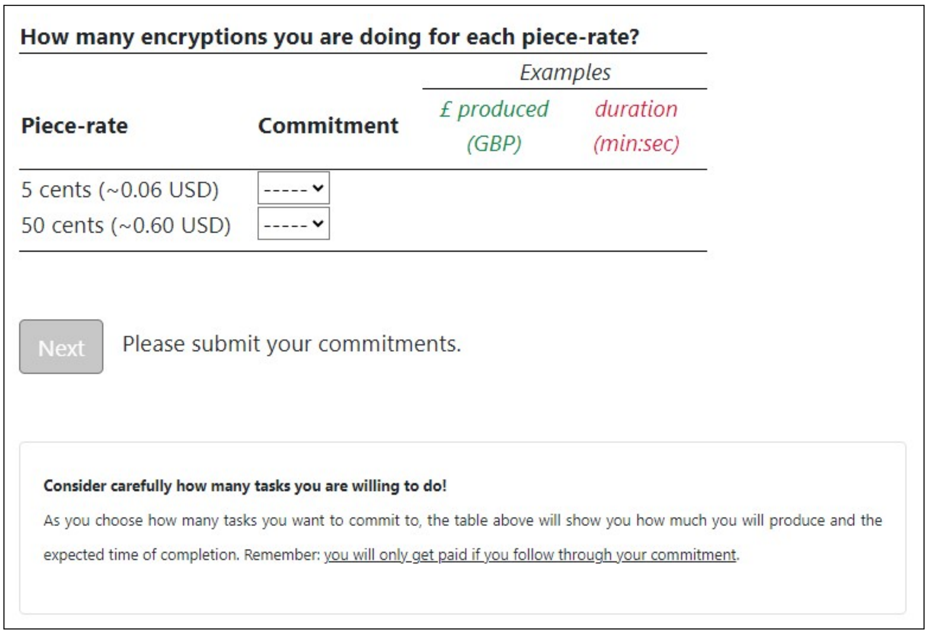
X	W	U	F	S	H	M	E	L	Q	D	J	Y
385	438	218	435	812	157	873	389	573	392	720	214	158

Notes: This screenshot exemplifies the letter-to-number encryption task. The encryption tables are depicted above. The table displays all letters of the English alphabet in random order. Each letter is allocated a 3-digit number. The assigned '*word*' and a filling blank for the '*code*' are depicted below. The 'code' is formed by all digits, with no space between them. Each round the '*word*' and encryption table are randomly chosen. The encryption table changes both the letter order and the numbers assigned to each letter. In this example, the '*word*' is XR and the '*code*' is 385054.

The encryptions take longer as participants advance. The first five encryption '*words*' have one letter. Every five encryptions one letter is added to the '*word*'. We inform participants about the increasing length of the '*word*' and exemplify it.

Task commitment. We inform participants about two possible piece-rate for each encryption succesfully completed: low piece-rate (£0.05, $\sim$ \$0.06), or high piece-rate (£0.50, $\sim$ \$0.60). We ask participants to commit to how many tasks they will complete under each piece-rate. The minimum number of tasks is 5, the maximum is 50. We ask participants to carefully consider their commitments, and inform them that they need to honor their commitment to receive the payment.

Figure D.2: Task commitment



Notes: This screenshot shows the explanation and form to commit tasks for each piece-rate payment. The last columns automatically generate estimates of money produced and total duration for the corresponding commitment.

Task completion. The resulting piece-rate is randomly assigned. Participants are required to honor their commitment to obtain the base payment.

Reward details. We inform participants their final payoff can be influenced by a third-party. We restrict information about when, how, why, and who is involved in the income allocation. Workers earn a £2 (∼ \$2.50) base payment and can earn bonus payment based on their performance.

C.2 Implementation

We recruited 40 participants in *Prolific* on August 2023. We offered a £2 (∼ \$2.50) base payment for completing the study and the possibility of earning additional money.[22] We set the expected time to complete the study to 10 minutes. Participation was available only to workers residing in the United States.

[22] *Prolific* works with British Pounds (£). Participants with sufficient experience in the platform are used to it. Still, we display an approximation for United States Dollars (\$) for the sake of clarity.

C.3 Results

The study was completed in 1 day. Median time to complete the study was 8 minutes and 32 seconds. Average payment to participants (including bonus payment) was £7.13 ($\sim$ \$8.55). Total cost was around £285 ($\sim$ \$340).

Table D.1: Sample characteristics

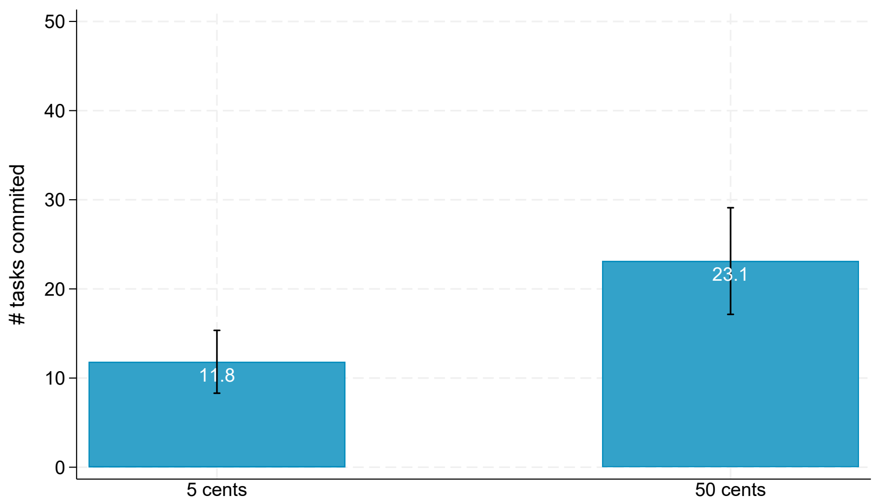
	Mean	Min	Max
	(1)	(2)	(3)
Panel A. Demographic			
Male	.47	.00	1.00
White	.53	.00	1.00
Age	36.89	20	76
Born in U.S.	.75	.00	1.00
Citizen from U.S.	.80	.00	1.00
Panel B. Performance			
Total approvals in Prolific	937	5	3,105
Time to complete task (seconds)	786	220	2,808
Total earnings from task	7.13	2.25	27.00

Notes: This table describes sample characteristics. Column (1) shows means. Column (2) shows minimum values. Column (3) shows maximum values.

Participants completed an average of 15.9 tasks (SD = 14.5).

Basic assumptions. Figure D.3 shows the mean task commitment for each piece-rate payment. Commitments for all piece-rate payments are statistically different from 5 and from 50 (see columns 2 and 3 in Table D.2 for details). Results are in line with the basic assumptions about worker's behavior.

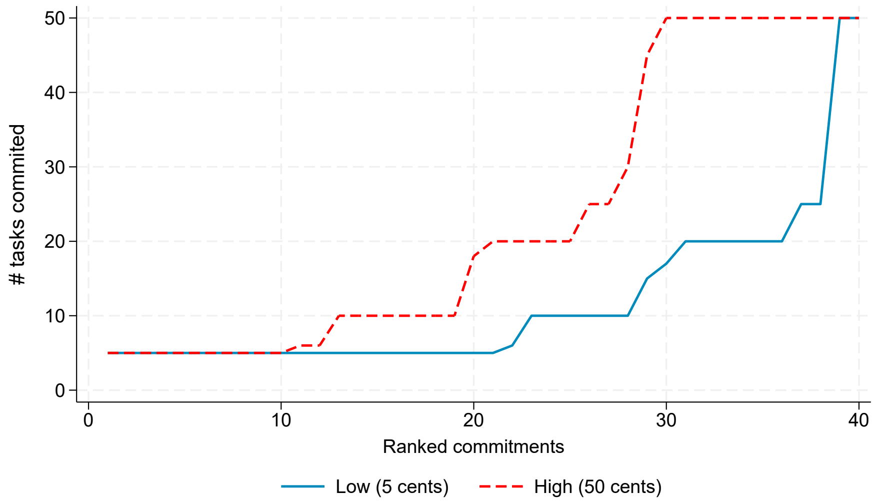
Figure D.3: Commitment by piece-rate payment



Notes: This figure plots mean task commitments for each piece-rate payment. 95% confidence interval is plotted as bars.

Implications. To explore commitment differences by piece-rate payments, we rank commitments within each piece-rate payment and compare the number of tasks committed in each ranking position. Figure D.4 depicts the results. There are workers committing the minimum and maximum number of tasks for all piece-rate payments. In those regions, commitments by piece-rate payments converge to the same number of tasks. For intermediate number of tasks, commitments are larger for the high piece-rate payment.

Figure D.4: Commitment ranking by piece-rate payment



Notes: This figure plots ordered task commitments for each piece-rate payment. Commitments are ranked within piece-rate payment (similar to a percentile). For example, rank 20 is the median task commitment for each piece-rate payment.

Column 4 in Table D.2 shows the differences for task compared to the high piece-rate payment. Commitments increase with the piece-rate payment. Raw differences are statistically significant.

We test the differences between task commitment by piece-rate payments using a regression. Results are shown in Table D.3. We run regressions comparing task commitment between low and high piece-rate payments. Commitments increase with the piece-rate payment. Differences are statistically significant for all specifications.

Table D.2: t-tests on commitments by piece-rate payment

	Mean	vs. 0	vs. 50	vs. High
	(1)	(2)	(3)	(4)
Low	11.8	-	-	-11.3***
		[.000]	[.000]	[.002]
High	23.1	-	-	
		[.000]	[.000]	

Notes: These tables describe participant's commitments for different piece-rate payments. Column (1) show mean commitment per piece-rate payment. Columns (2) and (3) show p-values on the differences with the minimum commitment (0 encryptions) and the maximum commitment (50 encryptions), respectively. Column (4) show differences with the High piece-rate payment (50 cents). p-values are reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.3: Piece-rate payments drawn

	(1)	(2)
High	11.3***	11.3***
	(2.4)	(3.3)
Individual FE	No	Yes
Observations	80	80
R^2	.122	.787

Notes: This table reports the coefficients for high piece-rate payment on task commitment. The dependent variable is the number of tasks committed. The independet variable is a dummy variable for 'high' piece-rate payment. Low piece-rate payment is 5 cents. High piece-rate payment is 50 cents. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$