Specialisation and the Allocation of Credit: Understanding and Appreciating Others' Work*

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Abstract

With specialised roles, workers produce different outputs; limited understanding of others' work can therefore distort how contributions are assessed. We study this in a joint-production experiment where paired workers perform distinct, complementary tasks and one role faces a harder variant yielding lower observable output for equal time spent. We independently vary information about average task performance and first-hand exposure to the other role's task. Easy taskers claim and receive larger shares of surplus. Exposure, but not Information, reduces this advantage and leads to more equal allocations. The effect persists after accounting for perceived task difficulty and understanding, but is more substantially attenuated when accounting for deservingness judgements, suggesting that first-hand experience fosters appreciation of others' contributions in ways that abstract performance information does not. Exposure also reduces bargaining frictions and improves productivity over time. Our findings show how experiential learning can reshape perceptions of merit, with implications for coordination within organisations and, more broadly, for how unequal outcomes are evaluated in society.

JEL codes: C92, D23, D63, D83, D91

Keywords: Inequality, Specialisation, Fairness Judgements, Labour, Experiment

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1 Introduction

Specialisation raises productivity by allowing individuals to develop distinct skills and combine complementary inputs (Becker and Murphy 1992). However, it also creates informational asymmetries: individuals often have limited understanding of the constraints and processes underlying others' work (Bolton and Dewatripont 1994; Garicano 2000).

These asymmetries can distort assessments of contributions across specialised roles in joint production. With heterogeneous tasks, similar effort may generate systematically different observable outcomes, potentially directing credit towards work with more visible or readily evaluated output. Thus, equally essential contributions can become difficult to compare and may appear unequal. A better understanding of how other roles translate work into observable output can improve assessment, but will affect credit allocation only if workers also appreciate its relevance to judgements of deservingness. Without both understanding and appreciation, misallocation of credit may persist.

This raises two questions: (i) how does limited cross-role understanding affect credit allocation, and (ii) does trying to improve it through codified information or first-hand experience matter? Both modes can improve understanding of how other roles operate, but experience may additionally foster appreciation of others' contributions. These questions matter because limited understanding or appreciation may lead workers to form divergent views of what constitutes fair credit allocation. Because individuals value equity and fairness (Fehr and Schmidt 1999), such disagreements can reduce motivation (Gesiarz et al. 2020; Breza et al. 2018), increase turnover (Buttner and Lowe 2017; Cullen and Perez-Truglia 2022), and intensify conflict within teams (Lazear 1989; Smulowitz and Almandoz 2021).

To answer these questions, we design a laboratory joint-production environment with specialised roles differing in task and difficulty. Participants are randomly assigned to "Grid" or "Slider" professions and paired across professions. Within each pair, one profession faces a harder variant calibrated to yield lower observable output for the same time spent working. The participants' task scores are multiplied to determine a joint surplus, which they subsequently divide through a simultaneous-claims mechanism.

This environment combines *complementary*, *specialised* roles with a systematic difference in how their work translates into observable output, allowing asymmetries in credit allocation to emerge endogenously. Understanding these role-specific production differences is thus important for evaluating contributions across roles. We study two ways of acquiring this understanding. *Information* presents past average performance in each task, revealing systematic differences in

observable output across professions. *Exposure* gives participants first-hand experience with the other profession's task during a warm-up phase. A 2×2 design independently varies Information and Exposure, allowing us to compare codified performance information with first-hand experience and examine their effects on credit claims, bargaining outcomes, and productivity.

We have three main results. *First*, despite both roles being essential to joint production, the resulting difference in observable output generates persistent asymmetries in credit allocation. Easy taskers claim and receive larger shares of joint surplus, and their claims are more responsive to relative observed outputs. *Second*, Exposure, but not Information, leads participants to place greater weight on role-specific production differences. It reduces easy taskers' claims, slightly increases those of hard taskers, and produces more equal final allocations. Finite-mixture estimates suggest that this asymmetry reflects differences in fairness types: easy taskers more commonly base claims on observed outputs alone, whereas hard taskers more commonly favour equal division, leaving greater scope for Exposure to shift easy taskers' claims. *Third*, Exposure also improves efficiency: it reduces bargaining frictions and increases productivity over time among easy taskers.

These findings suggest that first-hand cross-role experience can foster greater appreciation of others' work, reduce frictions in dividing joint surplus, and improve its production. The mechanism appears to extend beyond factual understanding of how the other role operates: post-experiment measures of task understanding and perceived difficulty have limited explanatory power, accounting for less of the Exposure effect than measures of perceived deservingness. Exposure may therefore change not only what participants know about the other role, but also the value they attach to its contribution.

Our work relates to literature on surplus division and credit attribution in joint production.[1] Karagözoğlu and Riedl (2015) show that relative-performance information can increase disagreement over bargaining entitlements, so information need not produce a common view of fair division. Cappelen et al. (2007, 2010) document substantial heterogeneity in fairness ideals, ranging from equal division to meritocratic principles that reward observed contributions while discounting factors beyond individual control. Such principles may also be interpreted in self-serving ways depending on one's position (Ubeda 2014; Pham et al. 2026). Related work documents

[1] See Cappelen and Tungodden (2019); Mengel and Weidenholzer (2023); Almås et al. (2025) for reviews of fairness and distributive preferences. A central theme is that distributive judgements depend on perceived deservingness: support for redistribution varies with whether income is viewed as earned or unearned (Balafoutas et al. 2013; Durante et al. 2014; Gee et al. 2017; Lekfuangfu et al. 2023), and inequality is more accepted when it reflects factors within individual control (Konow 2000; Mollerstrom et al. 2015), consistent with the *accountability principle* (Konow 1996, 2003).

distortions in credit attribution associated with gender (Isaksson 2018; Kinnl et al. 2026; Sarsons et al. 2021), the recency of contributions (Baranski and Muñoz-Herrera 2024), and spillovers between teammates (Ozerturk and Yildirim 2025).

A complementary literature examines whether attention to unequal circumstances changes distributive choices. Amasino et al. (2024) show that randomly advantaged participants pay less attention to merit, while directing attention towards merit reduces self-serving allocations. Wiese et al. (2025) find that revealing non-winners' potential performance in unreceived opportunities increases redistribution towards them, while Andre (2025) shows that spectators often fail to account for constraints shaping effort unless given reliable individual counterfactual evidence. Beyond distributive settings, the mode of learning can also shape judgements: experience can produce different decisions from description (Hertwig et al. 2004), narratives can have more persistent effects than statistics (Graeber et al. 2024), and perspective-taking or empathy can affect judgements of others (Todd and Galinsky 2014; Kwon and Funaki 2023).

Relative to these literatures, our contribution is threefold. *First*, we introduce a joint-production environment with distinct, calibrated real-effort tasks whose outputs jointly determine surplus. This provides a flexible framework for studying how differentiated roles, learning, and institutions shape credit allocation, bargaining, and cooperation.[2] *Second*, we use this framework to identify a distinct source of friction in credit allocation. Whereas existing studies generally examine common-task environments, specialised production requires workers to assess contributions across qualitatively different roles without a natural basis for comparison. Limited cross-role understanding can therefore distort perceived contribution and generate asymmetries in credit allocation. *Third*, we compare codified information with first-hand exposure to examine whether making role-specific production differences explicit is sufficient to change credit allocation, or whether first-hand experience is needed to foster greater appreciation of others' contributions. Our results show that codified information can make these differences transparent without changing credit allocations, whereas first-hand experience does.

Our findings speak directly to how organisations manage informational asymmetries under specialisation. Standard approaches emphasise incentives, monitoring, and contracts (Holm-

[2]Existing experiments on fairness and credit allocation generally use induced-value or common-task real-effort environments; even richer contexts involving risk or needs (Cappelen et al. 2013a,b) rarely feature specialised production. Relatedly, Weidmann et al. (2026) introduce a collaborative-production environment with distinct tasks, but workers do not occupy fixed specialised roles. Their focus, however, is managerial quality rather than fairness or credit allocation: managers dynamically allocate team members across tasks, monitor progress, and motivate workers. To our knowledge, ours is the first surplus-division experiment with qualitatively distinct real-effort tasks whose outputs jointly determine surplus. The absence of a shared performance scale creates a natural barrier to cross-role understanding absent in common-task designs.

ström and Milgrom 1991; Rayo 2007), but these tools do not address a distinct friction: limited cross-role understanding may impede workers' appreciation of other roles. In our setting, making systematic differences in observable output across roles explicit does not change credit allocations. Performance measurement and transparency may therefore be insufficient (Bloom and Van Reenen 2010; Bernstein 2012), whereas practices that provide first-hand exposure to colleagues' work—such as job shadowing, cross-training, and temporary rotations—may foster cross-role appreciation more effectively (Marks et al. 2002; Thongpapanl et al. 2018).

The same mechanism may extend beyond organisations to how work is valued across occupations and social groups. Beliefs about others' effort and contribution to society can shape judgements of deservingness, acceptance of inequality, and support for redistribution (Piketty 1995; Alesina and Glaeser 2004; Alesina and Angeletos 2005; Benabou and Tirole 2006). Limited understanding or appreciation of others' work may therefore lead individuals to undervalue contributions that are less visible. Domestic labour and caregiving are salient examples: disproportionately undertaken by women, they remain poorly captured in conventional measures of economic activity (Goldin 1990; Folbre et al. 2013; Andrew et al. 2024). Although our experiment does not directly examine societal inequality, it identifies a channel through which specialisation across complementary roles in society may contribute to unequal recognition and valuation of work (Piketty 2014; Abbott 1988), while suggesting that mitigation may require more than just better information.

2 Experimental Design

Participants are randomly assigned to one of two professions, which they retain throughout the experiment. Each participant is paired with a partner from the other profession to complete a joint production task, with each profession performing its own specialised real-effort task. Joint output depends on both participants' performance. After production, pairs bargain over how to divide the earnings they jointly produced.

A key feature of the design is that the professions differ systematically in task difficulty. One profession faces a "harder" variant, generating lower observable average scores despite identical time spent. Because inputs are complementary, this asymmetry creates ambiguity about how credit for joint output should be assigned and, consequently, about earnings division.

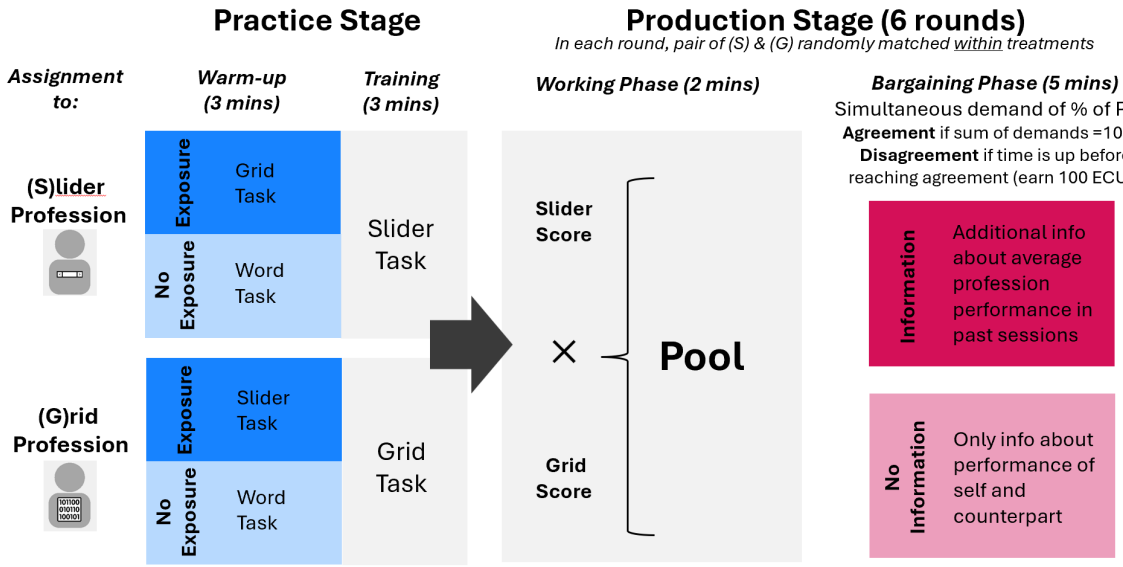
We study two interventions designed to improve cross-profession understanding. The Exposure treatment gives participants first-hand experience with the other profession's task during a practice stage. The Information treatment gives participants average past performance statistics

for each profession during bargaining. Both interventions make task difficulty salient, but only Exposure provides experiential knowledge that may further affect fairness judgements.

The experiment follows a 2×2 between-subjects design, varying Exposure and Information independently. Figure 1 Panel A shows the general flow of the experiment.

Figure 1: Summary of Experiment

Panel A: Experiment Flow



Panel B: Task Variants

	Easy	Hard
Grid Task	(3 × 3) Grid Avg Score: 25.0	(4 × 4) Grid Avg Score: 14.5
Slider Task	(Within 5 units) Avg Score: 23.0	(Within 2 units) Avg Score: 15.6

Panel C: Assignment to treatments

	No Info	Info
No Exp	$n = 144$	$n = 98$
Exp	$n = 116$	$n = 84$

Notes: Panel A summarises the experimental flow. Panel B reports mean numbers of correct responses per minute from pilot sessions with 44 participants; these values were displayed in the Information condition. In each session, one profession was assigned the hard variant and the other the easy variant, with sessions assigned either to Hard Grid–Easy Slider or Easy Grid–Hard Slider. Panel C reports participant counts by treatment condition.

2.1 Professions

Grid and Slider Tasks

At the start of the experiment, participants are randomly assigned to a *Grid* or *Slider* profession, indicated by distinct on-screen icons. A participant's profession determines which real-effort task they perform throughout the experiment. These tasks were chosen because they allow precise difficulty calibration and are relatively gender-neutral (Charness et al. 2018; Lezzi et al. 2015).

In the Grid Task (Abeler et al. 2011), participants see an $n \times n$ grid containing randomly arranged 0s and 1s and must count the number of 1s. Difficulty varies with the grid size n. In the Slider Task (Gill and Prowse 2011), participants see a horizontal line from 0 to 100 and must position a slider—whose exact position is not shown—within e units of a randomly determined target. Difficulty varies with required accuracy e. In both tasks, participants attempt as many questions as possible within a fixed time. Participants advance only after a correct response and scores equal the number of questions correctly solved.[3]

Task difficulty

Each task has two difficulty variants—*easy* and *hard*—which are fixed throughout the session. For the Grid Task, grid size n is 3 (easy) or 4 (hard). For the Slider Task, required accuracy e is 5 (easy) or 2 (hard). These were calibrated in pilot sessions such that average scores per minute are similar across easy variants and across hard variants, see Figure 1 Panel B.

In each session, one profession is assigned the hard variant and the other the easy variant. Thus, pairs always consist of one easy tasker and one hard tasker. The hard variant is not intended to reflect greater skill or expertise; rather, it is calibrated so that the same time spent tends to generate less *observable output*. Indeed, even relatively high scores in the hard variant are low compared to performance in the easy variant: 92% of easy taskers scored above the 90th percentile of hard-task performance.

[3] In the Grid Task, incorrect answers prompt participants to try again. In the Slider Task, participants are also told whether their selected position was too high or too low. Participants facing the same task variant always receive the same ordered sequence of questions, minimising variation from random task generation. Requiring correct answers before advancing also prevents strategic skipping of difficult questions.

2.2 Practice Stage

After assignment to their profession, participants complete a practice stage consisting of a warm-up followed by training.[4]

During the three-minute warm-up, participants perform a task unrelated to their assigned profession. The warm-up task depends on the Exposure treatment: In *No-Exposure*, participants complete a neutral word task in which they identify the nth letter of a given word. In *Exposure*, participants instead complete the task and difficulty variant associated with the other profession.[5] During training, participants practice their own task for three minutes before production.

2.3 Production Stage

The production stage consists of six rounds. In each round, participants are randomly matched with a partner from the opposite profession, so every pair includes one worker from the Grid profession and another from the Slider profession.

Working Phase

In the working phase, each participant performs their profession's task for two minutes. Individual scores equal the number of correct responses. The pair's joint output is the *product of their two individual scores*. This production function captures complementarity between specialised inputs: output depends symmetrically on both professions, so neither specialist can generate output alone.

Because task difficulty differs within pairs, hard taskers typically score lower despite identical time spent. This isolates a feature of specialised work: roles may generate different amounts of observable output even when their separate inputs are necessary for joint production. The asymmetry creates ambiguity over relative contributions and, consequently, over what constitutes a fair division of joint output or credit.

[4] Although unpaid, participants actively engage in the practice stage. Warm-up performance correlates with subsequent performance, suggesting it captures general ability or motivation. Training performance also strongly correlates with subsequent performance and can be interpreted as a task-specific ability measure.

[5] For example, participants facing the hard Grid task warm up with the easy Slider task, while participants facing the easy Grid task warm up with the hard Slider task.

Bargaining Phase

After the working phase, participants observe both individual scores and the resulting joint output. In *Information*, they also observe the average score per minute for each profession, based on data from pilot sessions.[6] Participants in *No-Information* receive no additional information.

Participants then bargain over how to divide joint earnings using a simultaneous-claims mechanism. Each participant demands a share of joint output in 5-percentage-point increments. If demands sum to 100 percent, agreement is reached and earnings are split accordingly. Otherwise, participants proceed to another bargaining round. Bargaining continues until agreement or a five-minute limit is reached, in which case both participants receive a fixed outside option of 100 ECUs. The mechanism, adapted from Karagözoğlu and Riedl (2015), avoids proposer advantages and allows us to observe both initial claims and adjustment dynamics during disagreement.

The bargaining task is intended to provide a behavioural measure of credit allocation rather than reproducing a specific wage-setting institution. Our primary outcome is the initial claim, which captures the share of joint output participants demand before observing their partner's claim or making concessions. Final shares are also informative, but they reflect both perceived entitlement and subsequent bargaining dynamics.

At the end of each bargaining phase, participants report perceptions of their own and their partner's effort, performance, and the fairness of the outcome.

2.4 Experiment Procedures

A total of 442 participants were recruited via mass emails at Nanyang Technological University, Singapore and participated in 18 sessions conducted in August and September 2023. Sessions averaged 24.6 participants and were randomly assigned ex ante to one of the four treatments.[7] The experiment was programmed in z-Tree (Fischbacher 2007) and received ethical approval from the university (IRB-2023-118). Figure 1 Panel C reports sample sizes by treatment.

At the beginning of each session, participants were seated at visually isolated computer terminals and received written instructions explaining the production and bargaining tasks, which were

[6] Specifically, participants are shown the relevant Easy Grid–Hard Slider or Hard Grid–Easy Slider averages from Figure 1 Panel B.

[7] Unequal treatment sample sizes reflect exclusion of sessions with software or computer malfunctions. Appendix Table A.1 reports participant demographics across treatment conditions. Demographics are generally similar, although Pearson χ^2 tests indicate differences in nationality and school; these tests should be interpreted cautiously because some categories have small cell counts. Our main treatment-effect estimates are robust to including demographic controls, including gender, academic year, nationality, and school (Appendix Tables B.1 and B.2).

read aloud by the experimenter.[8] Participants completed comprehension questions and proceeded only after answering all correctly. They were then assigned to professions and completed the practice and production stages. A final questionnaire then elicited participants' views on the joint task, perceived closeness to their counterparts and professions, and the perceived relationship between the professions. Appendix F provides the full instructions, experimental screenshots, and post-experiment survey.

Sessions lasted approximately 90 minutes. Participants were paid for two randomly selected production rounds and ECUs were converted at a rate of 100 or 140 ECUs to 1 SGD.[9] Including a 4 SGD show-up fee, average earnings were approximately 17.9 SGD.

3 Conceptual Framework

3.1 Joint production

We develop a simple framework of fairness judgements across specialised roles to generate experimental predictions. Two workers perform distinct tasks, indexed by $i \in \{1, 2\}$. Worker i produces observable output q_i, and joint surplus is given by $V(\mathbf{q})$, where $\mathbf{q} \equiv (q_1, q_2)$. Joint surplus is increasing in each input, with $V_i > 0$ for each i.

Without loss of generality, we assume that average observable output is higher in task 1 than in task 2: $\bar{q}_1 > \bar{q}_2 > 0$. This captures a central feature of our experiment: the easy task variant generates systematically higher observable output than the hard task variant despite identical time spent on the task.

3.2 Preferences over allocation

After observing both individual outputs, workers bargain over how to allocate joint surplus $V(\mathbf{q})$. Following Cappelen et al. (2010), we assume that claims reflect both material self-interest and

[8] Written instructions covered the overall structure of the experiment, while treatment-specific manipulations were implemented primarily through the experimental interface. In Information, average performance statistics were displayed during the bargaining phase. In Exposure, participants were guided through the warm-up task in the interface.

[9] Two earlier sessions used 100 ECUs per SGD; all other sessions used 140 ECUs per SGD. Procedures were otherwise identical, and analyses include exchange-rate fixed effects to control for this.

fairness concerns. When making a claim $y_i \leq V(\mathbf{q})$, worker i solves:

$$\max_{y_i} \quad y_i - \beta \left[\frac{\big(y_i - m_i(\mathbf{q})\big)^2}{2V(\mathbf{q})} \right],$$

where $m_i(\mathbf{q})$ is worker i's perceived fair allocation, and the bracketed term captures the disutility from deviating from this perceived fair allocation. $\beta > 0$ measures the weight placed on fairness relative to material payoffs.

For an interior solution, the optimal claim is:

$$y_i^* = m_i(\mathbf{q}) + \frac{V(\mathbf{q})}{\beta}.$$

Claims thus exceed perceived fair allocations by a self-interest markup that shrinks as fairness concerns strengthen.

3.3 Perceived Fair Allocations

We assume that workers hold meritocratic fairness ideals, under which larger contributions are perceived to deserve larger shares of joint surplus. Workers may differ, however, in whether they evaluate contributions using raw observed outputs or outputs adjusted for task difficulty. We capture this by modelling worker i's perceived fair allocation as a convex combination of two meritocratic benchmarks:

$$\begin{aligned} m_i(\mathbf{q}) = (1 - \alpha_i) &\left[\frac{q_i}{q_1 + q_2} V(\mathbf{q}) \right] \\ &+ \alpha_i \left[\frac{q_i/\bar{q}_i}{q_1/\bar{q}_1 + q_2/\bar{q}_2} V(\mathbf{q}) \right]. \end{aligned}$$

The first term is *surface-level meritocracy*, which evaluates contributions in proportion to observed output alone. The second is *weighted meritocracy*, which evaluates contributions based on observed output relative to average performance in each task.

The parameter $\alpha_i \in [0, 1]$ captures the degree of *cross-role adjustment*: the weight worker i places on role-specific differences in how work translates into observable output. Higher values imply greater adjustment; lower values reflect stronger reliance on raw observed output. Behaviourally, α_i may reflect both understanding of how the other role operates and appreciation of why these differences matter for deservingness.

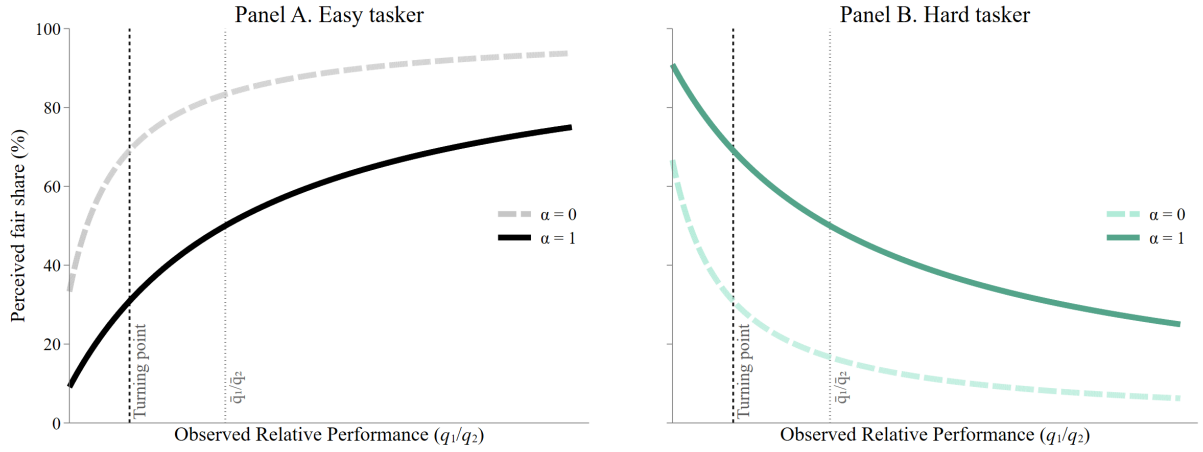
This formulation allows fairness judgements to differ across workers. Because surface-level meritocracy favours easy taskers, they may exhibit less cross-role adjustment than hard taskers. Such differences can shape claims and generate disagreement over fair allocations even when both workers observe the same outputs and joint surplus. In our experiment, Information and Exposure may increase cross-role adjustment through different channels: both may improve understanding of how the other role operates, while Exposure may additionally foster appreciation of the other role's contribution.

Our main framework focuses on meritocratic fairness ideals because these are most directly affected by cross-role adjustment and therefore generate directional empirical predictions. These predictions remain informative as long as meritocratic ideals are sufficiently common. Other fairness ideals, such as strict egalitarianism, may also shape claims and attenuate the effects of cross-role adjustment. Appendix E.2 develops this extension.

3.4 Comparative statics

Figure 2 illustrates how perceived fair shares vary with observed relative performance under surface-level ($\alpha_i = 0$) and weighted meritocracy ($\alpha_i = 1$).

Figure 2: Perceived fair shares under surface-level and weighted meritocracy



Notes: The figure plots perceived fair shares as a function of q_1/q_2, the observable output of the easy tasker relative to that of the hard tasker. Dashed curves represent surface-level meritocracy ($\alpha = 0$), while solid curves represent weighted meritocracy ($\alpha = 1$). The dashed vertical line marks $q_1/q_2 = \sqrt{\bar{q}_1/\bar{q}_2}$, where the gap between the two benchmarks is greatest; the dotted vertical line marks average relative performance, $q_1/q_2 = \bar{q}_1/\bar{q}_2$, at which weighted meritocracy assigns each worker 50% of the joint surplus. Appendix E provides the formal derivations.

Both benchmarks are meritocratic, so higher $\frac{q_1}{q_2}$ increases the perceived fair share of the easy tasker while decreasing that of the hard tasker. The benchmarks differ, however, in how they

interpret the easy tasker's observed output advantage. By accounting for task difficulty, weighted meritocracy discounts this advantage, lowering perceived fair shares for easy taskers and raising them for hard taskers. The difference between the two benchmarks is largest at intermediate relative performance, where the source of the easy tasker's advantage is most ambiguous.[10]

3.5 Predictions

The framework yields a baseline implication for credit allocation across roles. Because easy taskers generate more observable output on average, surface-level meritocracy assigns them larger fair shares than hard taskers. Weighted meritocracy attenuates this advantage by evaluating output relative to average performance within each task. Thus, to the extent that workers place weight on observed output alone, easy taskers should claim more than hard taskers on average.

Information and Exposure may both increase cross-role adjustment through greater understanding of how work translates into output across roles. In terms of the framework, greater cross-role adjustment increases α_i, shifting perceived fair shares away from surface-level meritocracy and towards weighted meritocracy. We therefore predict the following:

Prediction 1. *In the Information and Exposure conditions, easy taskers claim a lower proportion, while hard taskers claim a higher proportion.*

We further expect stronger effects from Exposure because, beyond improving understanding, first-hand experience may be more vivid, credible, and conducive to perspective-taking. Consequently, it may additionally foster greater appreciation of others' contributions. We therefore predict the following:

Prediction 2. *Effects on claims are larger in the Exposure condition than in the Information condition.*

Heterogeneous Treatment Effects

The framework also suggests treatment heterogeneity by worker role and observed relative performance, which we explore empirically.

[10] Formally, the gap between surface-level and weighted meritocracy is increasing in observed relative performance up to $q_1/q_2 = \sqrt{\bar{q}_1/\bar{q}_2}$ and decreasing thereafter. Because $\bar{q}_1/\bar{q}_2 > 1$, this threshold is below average relative performance. Beyond this point, higher relative performance increasingly reflects contribution beyond the easy task's average advantage, making weighted fair shares more sensitive to relative performance and narrowing the gap between the two benchmarks.

(i) Role heterogeneity. We first examine whether treatment effects differ between easy and hard taskers. Role differences may arise because task roles shape which fairness ideals are more favourable. Since surface-level meritocracy favours easy taskers, whose observable output is higher by design, they may have greater scope to revise their claims when task difficulty becomes salient. Hard taskers, by contrast, may already make claims closer to weighted meritocracy or equality, leaving less room for Information or Exposure to increase their claims.

(ii) Relative-performance heterogeneity. We also examine whether treatment effects vary with observed relative performance. The comparative statics suggest that effects may be larger in the intermediate range, where the easy tasker's output advantage is most open to competing interpretations.

4 Results

Our analysis uses the $442 \times 6 = 2{,}652$ individual-round observations generated during the production stage, corresponding to 1,326 pair-round observations involving one easy and one hard tasker. Because treatments were assigned at the session level and random rematching across rounds induces dependence among observations within sessions, our main specifications include session random effects and report standard errors clustered at the session level.[11]

Before turning to treatment effects, we first document baseline patterns in production and bargaining. Table 1 Panel A shows that our difficulty manipulation generates a large difference in observable output: easy taskers achieve substantially higher scores than hard taskers. This output asymmetry is reflected in bargaining. In the initial bargaining round, easy taskers claim 63.3% of the joint surplus on average, well above an equal split. By contrast, hard taskers claim 48.5% on average, close to an equal split. The two initial claims exceed the available surplus in 77% of pairs, although 96% ultimately reach agreement before the bargaining time limit.[12] Final allocations continue to favour easy taskers, who receive larger shares of joint surplus and earn more as a result. Figure A.1 shows that this inequality is pervasive: across all performance

[11] Appendix Table B.3 compares our main estimates with alternative OLS specifications using two-way clustering by easy- and hard-tasker identifiers or session-clustered standard errors, and additionally reports wild-cluster-bootstrap p-values at the session level to account for the relatively small number of sessions. The pattern of results is robust across these approaches, with only modest changes in statistical significance under wild-cluster-bootstrap inference.

[12] In approximately 8% of pairs, combined initial claims sum to less than 100% and therefore also fail to produce agreement.

Table 1: Descriptive statistics by task difficulty

	Easy	**Hard**	**Difference**
Panel A: Outcomes	*mean (sd)*	*mean (sd)*	*b (se)*
Individual Score	56.872	32.532	24.339***
	(10.874)	(6.867)	(0.667)
Initial Claim	63.314	48.454	14.860***
	(9.898)	(8.715)	(1.125)
Final Share	56.412	43.588	12.824***
	(7.163)	(7.163)	(0.944)
Earnings	1015.477	791.386	224.091***
	(383.856)	(322.958)	(13.378)
"Own task is harder"	2.914	6.661	-3.747***
	(1.510)	(0.819)	(0.147)
"Put in more effort than counterpart"	4.611	4.597	0.014
	(1.777)	(1.586)	(0.161)
Panel B: Responsiveness of Initial Claims to Score Ratio (Easy Score/Hard Score)	*b (se)*	*b (se)*	*b (se)*
$\beta_{ScoreRatio}$	6.790***	-2.288*	
	(0.826)	(1.003)	
$\lvert\beta_{ScoreRatio}\rvert$	6.790***	2.288*	4.502***
	(0.826)	(1.003)	(1.137)

Notes: Panel A reports means, with standard deviations in parentheses, separately for easy and hard taskers. Individual Score, Initial Claim, Final Share, and Earnings use individual-round observations; the two survey outcomes use individual-level observations and are measured on seven-point scales. Final Share excludes pairs that did not reach agreement. Tests of differences use session clustered standard errors. Panel B reports coefficients from a session random effects regression allowing separate intercepts and score-ratio slopes for easy and hard taskers. The score ratio is the easy tasker's score divided by the hard tasker's score. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

deciles, easy taskers earn significantly more than hard taskers ($p < 0.001$). Specialised production can therefore generate systematic asymmetries in credit allocation favouring the role with higher observable output.

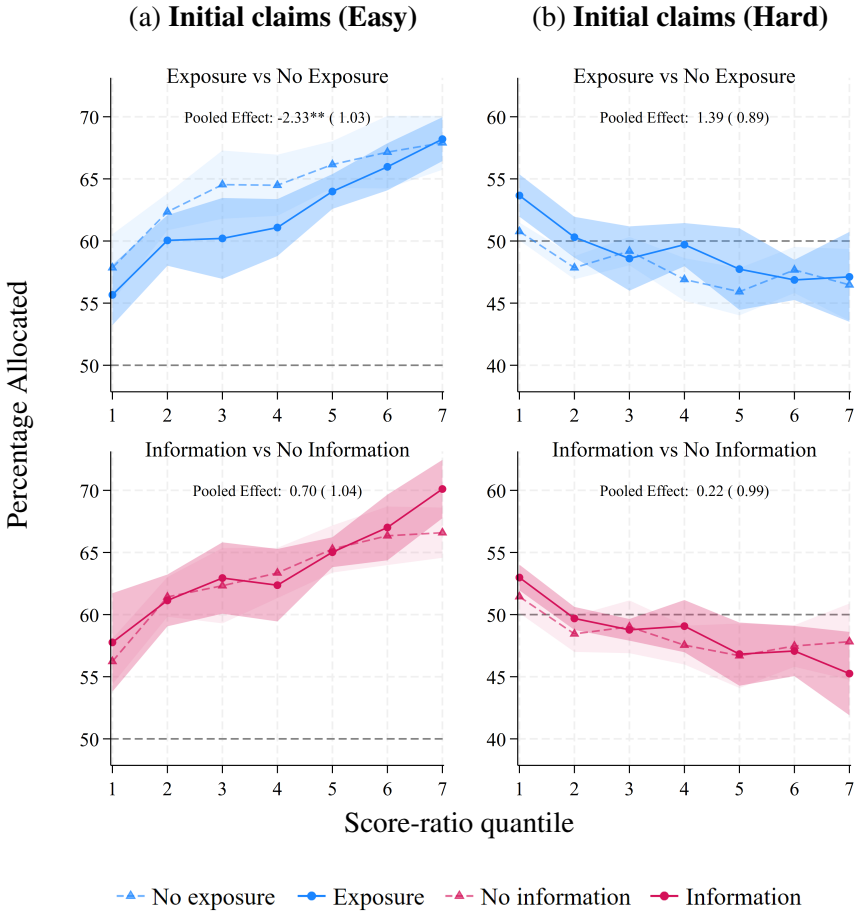
Post-experiment responses indicate that by the end of the experiment, both easy and hard taskers recognise the difficulty asymmetry, although hard taskers express this belief more strongly.[13] Participants do not, however, report systematic differences in perceived effort across roles. Table 1 Panel B also indicates that claims respond differently to relative performance across roles: easy taskers' initial claims have a steeper relationship with relative performance than hard taskers' claims ($p < 0.001$).

[13]Hard taskers' ratings are further from neutral than easy taskers' ratings ($p < 0.001$).

In contrast to the pronounced differences by task difficulty, Table A.2 shows only modest differences between Grid and Slider specialists, consistent with task difficulty, not task type, as the main source of asymmetry. Overall, these baseline patterns show that when specialised roles differ in how effort translates into observable output, credit allocation tilts towards the role with higher observable output. We next examine whether Exposure and Information mitigate this.

4.1 Effects of Exposure and Information

Figure 3: Treatment effects on initial claims across score-ratio quantiles



Notes: Each panel shows (1) predicted margins for Exposure/No Exposure or Information/No Information at each quantile of the score ratio, with 95% confidence intervals, and (2) the pooled effect of Exposure or Information, with standard errors in parentheses. Standard errors are clustered at the session level. Exposure comparisons average over Information conditions, while Information comparisons average over Exposure conditions. Estimates are derived from the regressions in Tables A.3 and A.4 (Columns 1 and 2), which report specifications without and with treatment interactions with score-ratio quantiles, respectively. All panels use the same y-axis span and display a 50% reference line for comparability.

We estimate treatment effects by regressing initial claims and final shares on Exposure and Information, controlling flexibly for observed relative performance using indicators for seven quantiles of the score ratio. All specifications control for round, task (grid/slider), and exchange-rate fixed effects, as well as joint earnings. Figure 3 presents the key estimates from these regressions.

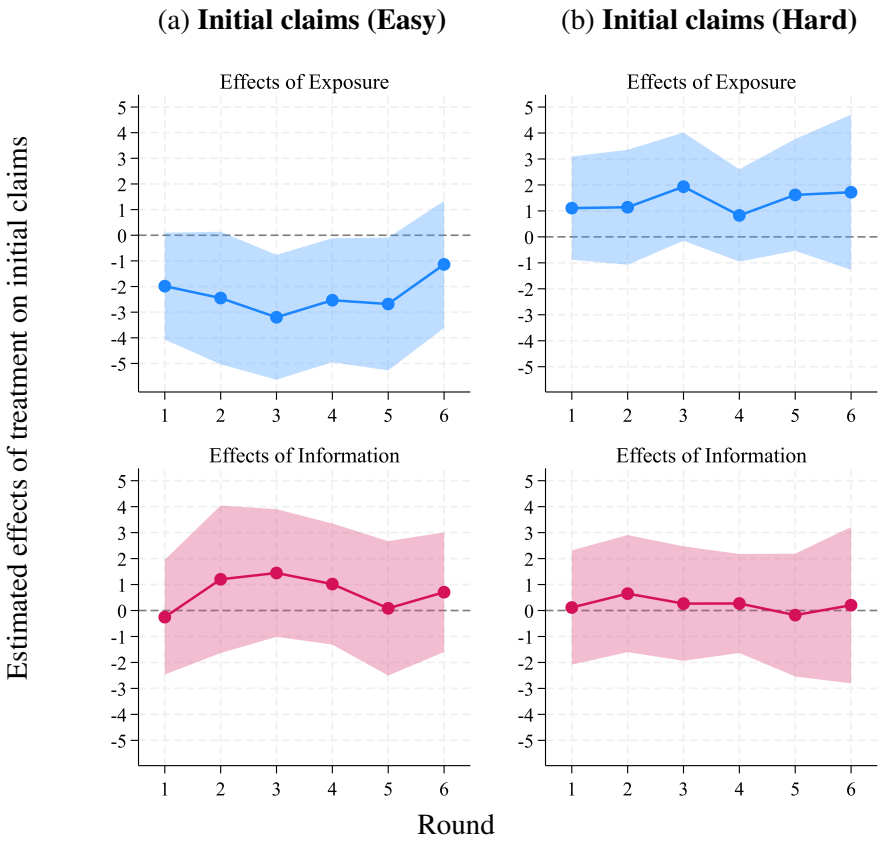
Prediction 1 states that Information and Exposure should increase cross-role adjustment, reducing claims by easy taskers and increasing claims by hard taskers. Figure 3 shows support for this prediction primarily for Exposure and among easy taskers. In Panel A, Exposure reduces easy taskers' initial claims by 2.3 percentage points in the pooled specification ($p = 0.024$). Effects are most pronounced at intermediate levels of relative performance: in score-ratio quantiles 3 and 4, Exposure reduces claims by 4.3 and 3.4 percentage points ($p = 0.041$ and $p = 0.046$, respectively). The differences then narrow towards the highest quantiles. In Panel B, hard taskers' initial claims increase by 1.4 percentage points under Exposure, but not significantly ($p = 0.120$). Notably, estimated effects are again small in the highest quantiles.

Information has no discernible pooled effect on initial claims for either easy taskers ($p = 0.502$) or hard taskers ($p = 0.822$). Consistent with Prediction 2, the pooled effects of Exposure and Information differ for easy taskers ($p = 0.046$), suggesting that first-hand experience is more influential than codified performance information in shaping claims.

Effects over time

A potential concern is that Information has no effect because it becomes redundant as participants accumulate observations of partners' performance over successive rounds. If so, we should observe a negative effect of Information in the early rounds that attenuates as participants in the baseline accumulate their own observations of partners' performance. To examine this possibility, Figure 4 plots the estimated effects of the Exposure and Information treatments in each round. The results do not support this interpretation. Among both easy and hard taskers, the estimated Information effect is small and statistically insignificant in the first production round and does not subsequently exhibit the progressive attenuation that this explanation would predict. By contrast, the Exposure effect for easy taskers is already negative in the first round and remains negative throughout the experiment. The estimated Exposure effect for hard taskers is also positive in every round, although the individual round estimates are generally imprecise.

Figure 4: Treatment effects on initial claims across rounds

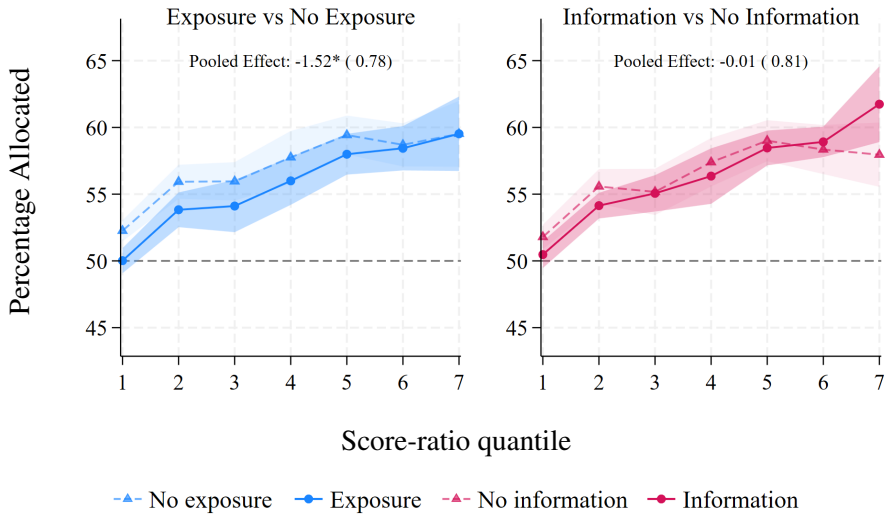


Notes: Points show the estimated effects of Exposure (top) and Information (bottom) on initial claims in each production round, separately for easy and hard taskers; shaded areas indicate 95% confidence intervals. Estimates are derived from regressions in Table A.5, which report specifications with treatments interacted with round dummies. Standard errors are clustered at the session level. Exposure effects average over Information conditions, while Information effects average over Exposure conditions. The dashed horizontal line denotes zero.

Effects on final shares

Turning to final allocations, Figure 5 shows effects that are qualitatively similar to those for initial claims, although somewhat attenuated. Among pairs that reach agreement, Exposure reduces easy taskers' final share by 1.5 percentage points in the pooled specification ($p = 0.051$). This smaller effect is consistent with final shares reflecting both initial claims and subsequent bargaining. Information has no discernible effect on final shares. Easy taskers nevertheless continue to receive more than half of the joint surplus in every score-ratio quantile.

Figure 5: Treatment effects on final shares (easy)



Notes: Each panel shows (1) predicted margins for Exposure/No Exposure or Information/No Information at each quantile of the score ratio, with 95% confidence intervals, and (2) the pooled effect of Exposure or Information, with standard errors in parentheses. Standard errors are clustered at the session level. Exposure comparisons average over Information conditions, while Information comparisons average over Exposure conditions. Estimates are derived from the regressions in Tables A.3 and A.4 (Column 3), which report specifications without and with treatment interactions with score-ratio quantiles, respectively. All panels use the same y-axis span and display a 50% reference line for comparability. Final shares include only pairs that reached agreement.

Interaction between Exposure and Information

We also examine whether Exposure and Information reinforce each other. Appendix B reports specifications including their interaction, motivated by evidence that statistical information can amplify experiential interventions (Andries et al. 2026). Although some coefficients have signs consistent with reinforcement, none are statistically significant, providing little evidence that the two interventions interact.

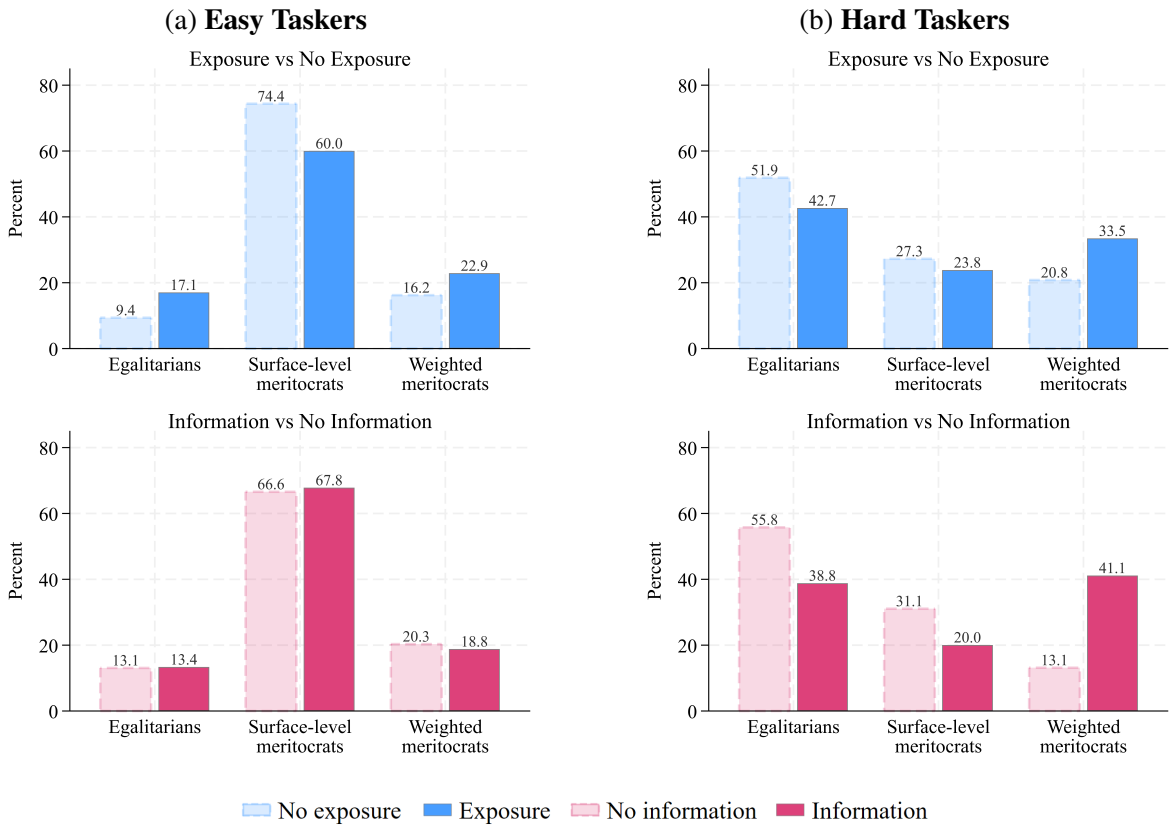
4.2 Mechanisms

Heterogeneity in fairness ideals

Taken together, the preceding results indicate that Exposure is more effective than Information in shifting credit allocation away from surface-level meritocracy, particularly among easy taskers. The weaker and less precise effects for hard taskers may reflect heterogeneity in underlying fairness ideals. Hard taskers' claims are both closer to an equal split and less sensitive to relative performance across treatments, a pattern that is not naturally explained by greater cross-role

adjustment alone within our conceptual framework.[14] Because hard taskers are disadvantaged in observable performance in 98% of rounds, they may instead rely more on egalitarian or other non-meritocratic principles, leaving less scope for Exposure or Information to shift their claims upward. Appendix E.2 discusses this possibility theoretically.

Figure 6: Exposure, Information and estimated fairness types



Notes: Bars report estimated probabilities of three latent fairness types obtained from the finite-mixture model: egalitarians, surface-level meritocrats, and weighted meritocrats. Types are estimated at the individual level using each participant's six initial claims. Exposure comparisons average over Information conditions, while Information comparisons average over Exposure conditions. Appendix C describes the estimation procedure; Tables A.6 and A.7 report the underlying estimates.

To directly examine this, we estimate a finite mixture model (FMM) that classifies participants into three latent fairness types: (i) *egalitarians*, who prefer a 50-50 split; (ii) *surface-level meritocrats*, who favour a share proportional to $\frac{q_i}{q_1+q_2}$; and (iii) *weighted meritocrats*, who favour

[14] In our framework, greater cross-role adjustment (a higher α_i) moves hard taskers' perceived fair shares closer to 50–50 at average relative performance, while also making their perceived fair shares more sensitive to relative performance over a broad range around the mean. See Figure 2 and footnote 10 for the relevant comparative statics.

a share proportional to $\frac{q_i/\bar{q}_i}{q_1/\bar{q}_1+q_2/\bar{q}_2}$. Appendix C describes the estimation procedure in detail. Table A.6 reports the full set of estimated parameters, while Figure 6 summarises the main patterns.[15]

The estimated types clarify the asymmetry between easy and hard taskers. Among easy taskers, surface-level meritocrats are the most prevalent type. Among hard taskers, egalitarians are the most prevalent type, consistent with their lower sensitivity to relative performance. Exposure reduces the share of surface-level meritocrats among easy taskers by 14.3 percentage points ($p = 0.040$), mirroring the decline in their initial claims. Information has no corresponding effect for easy taskers ($p = 0.860$). For hard taskers, both Exposure and Information are associated with a lower share of egalitarians and a higher share of weighted meritocrats, with the Information effect particularly pronounced. However, this shift is unlikely to produce a commensurate change in hard taskers' claims because, for them, egalitarian and weighted-meritocratic claims are often relatively similar.

Survey Evidence

Is Exposure operating purely by improving understanding of task difficulty? The round-by-round results in Figure 4 provide little evidence that Exposure operates simply by accelerating learning about task difficulty. Its effect on easy taskers' claims is already present in the first production round and remains negative throughout the experiment.

Post-experiment survey responses provide complementary evidence. By the end of the experiment, participants across all treatments recognise the difficulty asymmetry: on a 1–7 scale, easy taskers tend to disagree that their task is more difficult (mean = 2.91), while hard taskers strongly agree (mean = 6.66), with responses differing significantly from neutrality in all treatment arms ($p < 0.001$). Exposure nevertheless affects some measures of task understanding: easy taskers report lower perceived difficulty of their own task and a stronger understanding of their counterpart's task in the Exposure condition, but not in the Information condition (Table A.8 Columns 3–4). Controlling for these measures, however, leaves the estimated effect of Exposure on easy taskers' initial claims largely unchanged (Table 2, Column 2).

Exposure also affects social closeness across professions. Easy taskers in the Exposure condition report greater closeness to their counterpart and a smaller difference between closeness to their own and the other profession (Table A.8, Columns 9–10). However, controlling for these measures again leaves the Exposure effect on initial claims largely unchanged (Table 2, Column 3). The evidence is more consistent with a change in perceived deservingness. Easy taskers in

[15] Appendix D presents an alternative classification based on minimum-distance assignment. Results are qualitatively similar, except that effects of Exposure and Information on hard taskers' fairness types are weaker.

Table 2: Mechanisms underlying the Exposure effect on initial claims

Dep Var:	Initial Claims (Easy Taskers)			
	(1) Baseline	(2) + Understanding	(3) + Closeness	(4) + Deservingness
Exposure	-2.332**	-2.169**	-2.037**	-1.596
	(1.032)	(1.044)	(1.027)	(0.998)
Info	0.699	0.789	0.679	0.773
	(1.042)	(0.962)	(1.080)	(0.948)
Task-understanding controls		✓		
Closeness controls			✓	
Perceived-deservingness control				✓
Joint Earnings	✓	✓	✓	✓
Round, Task, Exchange Rate Fixed Effects	✓	✓	✓	✓
Score-Ratio Fixed Effects	✓	✓	✓	✓
Observations	1326	1326	1326	1326

Notes: Session random-effects regressions using individual-round observations for easy taskers. Column (1) reports the baseline specification. Column (2) additionally controls for perceived difficulty of one's own task and reported understanding of the counterpart's task. Column (3) additionally controls for closeness to the counterpart and the difference between closeness to one's own and the other profession. Column (4) additionally controls for whether the participant believes their own task should earn more. Standard errors are clustered at the session level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Appendix Table A.9 reports the full specifications, including coefficients on the mechanism measures and corresponding estimates for hard taskers.

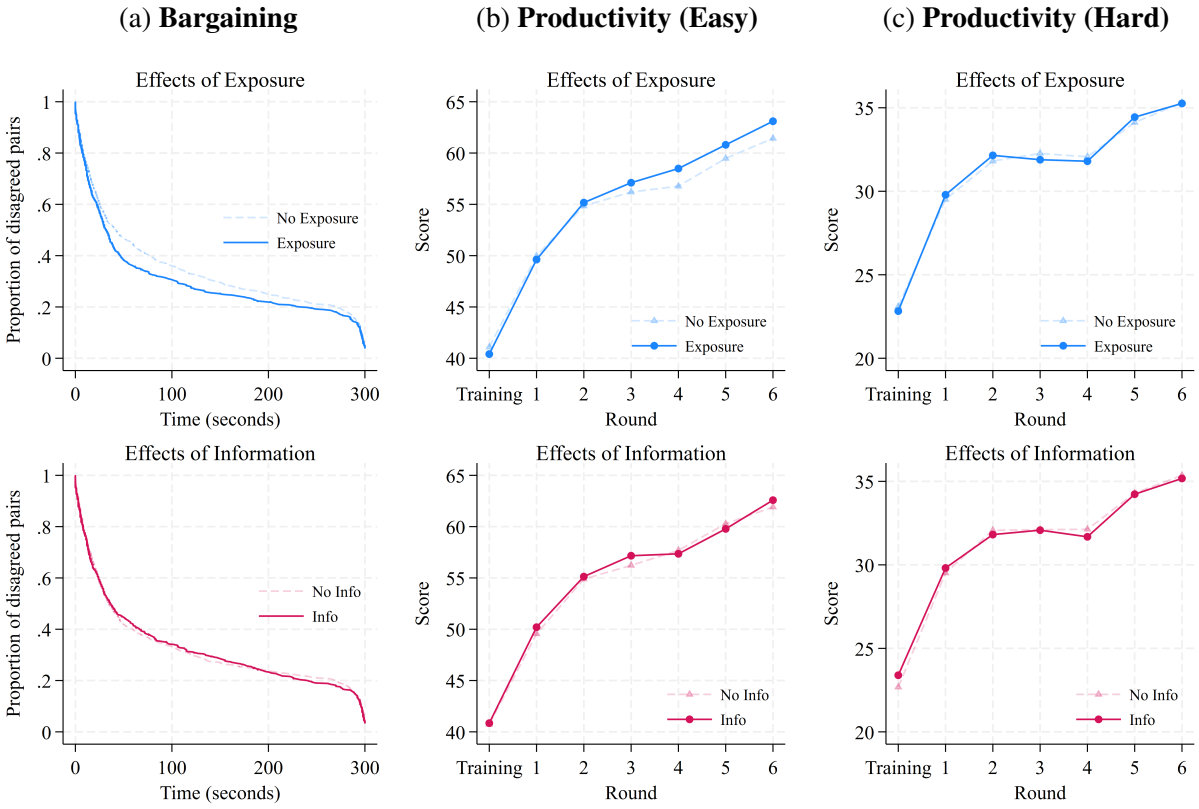
the Exposure condition are less likely to report that their task should earn a higher payoff (Table A.8, Column 5), and controlling for this measure attenuates the Exposure coefficient more substantially (Table 2, Column 4). In terms of our framework, these findings suggest that α_i, the degree of cross-role adjustment, depends not only on factual understanding of how another role operates, but also on appreciation of why that role's contribution matters for judgements of deservingness.

4.3 Additional effects on bargaining and productivity

Exposure also affects behaviour beyond the allocation of credit. Figure 7 summarises effects on bargaining and productivity. During bargaining, Exposure reduces the proportion of pairs that remain in disagreement throughout much of the bargaining process, whereas Information produces little discernible difference. Appendix Table A.10 shows that Exposure significantly reduces the number of bargaining rounds required to reach agreement ($p = 0.002$), while its effect on total bargaining time is negative but less precisely estimated. Information has no detectable

effect on either outcome.[16]

Figure 7: Treatment effects on other outcomes



Notes: Panel (a) plots the proportion of pairs that have not yet reached agreement and remain in the bargaining process at each elapsed second. The bargaining window ends after 300 seconds. Panels (b) and (c) plot mean task scores for the training round and the six production rounds, separately for easy and hard taskers. Exposure comparisons average over Information conditions, while Information comparisons average over Exposure conditions. Because the training round lasts three minutes and each production round lasts two minutes, training scores are multiplied by $\frac{2}{3}$ to ensure comparability.

Exposure also improves productivity over time, but primarily among easy taskers. Both easy and hard taskers become more productive across rounds, reflecting learning. Among easy taskers, however, performance improves more rapidly under Exposure. This divergence is not evident during the training stage and emerges only during production. Table A.12 reports a positive Exposure $\times$ Round interaction for easy taskers, but no comparable effect for hard taskers. By contrast, Information does not affect productivity trends for either role.

[16]Consistent with this faster convergence, Exposure also makes easy taskers more likely to reduce their claims following bargaining rounds in which they had claimed at least as much as hard taskers, while having no corresponding effect on hard taskers' upward adjustments (Appendix Table A.11).

Taken together, these patterns are consistent with first-hand experience doing more than conveying information: it may also improve participants' appreciation of their counterpart's role, reducing bargaining frictions and improving productivity.

5 Conclusion

Specialisation can make contributions across roles difficult to compare. In our experiment, differences in how specialised roles produce output generate persistent asymmetries in credit allocation—even when both roles are essential to joint production. More importantly, we show that understanding another role need not imply appreciating its contribution when judging deservingness. Statistical information makes these differences transparent but leaves credit allocations unchanged, whereas exposure reduces easy taskers' advantage, produces more equal allocations, reduces bargaining frictions, and improves productivity. First-hand experience therefore appears to change how contributions across roles are evaluated, not merely what participants know.[17]

These insights extend beyond the laboratory. In organisations, labour markets, and society, work may be undervalued when those allocating credit lack experience of what it entails or appreciation of its contribution. Shared experience may therefore provide a distinct channel for shaping judgements of merit and deservingness beyond transparency and performance information. More broadly, our findings may have political-economy implications. Because distributive preferences are linked to perceptions of the sources and fairness of inequality (Amasino et al. 2023; Valero 2022), exposure to different economic positions—for example through occupational or intergenerational mobility—could broaden appreciation of less advantaged positions and foster more egalitarian fairness judgements, in turn strengthening support for institutions that sustain such mobility.

Our design also provides a framework for studying credit allocation across qualitatively distinct yet complementary tasks. It can be used to examine how cross-role understanding interacts with self-serving interpretations (Babcock and Loewenstein 1997; Rodriguez-Lara and Moreno-Garrido 2012; Coutts et al. 2024), social relationships and organisational power (Ashforth and Mael 1989; Blau 2017), and gendered or racialised divisions of labour. Future work could extend the framework to managers or other third-party allocators who do not participate in production.[18]

[17] Participants also value cross-role understanding: on a 1–7 scale, they prefer partners who understand their work (mean = 6.02) and want to experience their colleagues' tasks (mean = 5.38), particularly among hard taskers.

[18] In our post-experiment survey, 87% preferred a "generalist" who had experienced both tasks to a specialist as a third-party allocator.

More broadly, it offers a way to study how organisational structures and evaluation systems shape recognition and reward under specialisation.

Declarations

The authors have no competing interests in the submission of this article. During the preparation of this work, the authors used ChatGPT (OpenAI) for two distinct purposes: (1) *Programming Assistance*: to assist with syntax troubleshooting and figure/table formatting within Stata, (2) *Language Editing*: to improve grammar and clarity after writing the full draft. All substantive content, argumentation, experimental design, econometric modelling, and framing reflect the authors' own thinking. After using this tool, the authors rigorously reviewed and edited the content as needed and take(s) full responsibility for the content of the published article. The authors have tested all Stata commands to ensure statistical validity and take full responsibility for the final content of the publication. This study was funded by the Ministry of Education (MOE) Tier 1 AcRF seed fund (RS 15/20).

References

Abbott, A. (1988). *The system of professions: An essay on the division of expert labor*. University of Chicago Press.

Abeler, J., Falk, A., Goette, L., and Huffman, D. (2011). Reference points and effort provision. *American Economic Review*, 101(2):470–492.

Alesina, A. and Angeletos, G.-M. (2005). Fairness and redistribution. *American Economic Review*, 95(4):960–980.

Alesina, A. and Glaeser, E. (2004). *Fighting Poverty in the US and Europe: A World of Difference*. Oxford University Press.

Almås, I., Hufe, P., and Weishaar, D. (2025). Experimental evidence on attitudes toward inequality and fairness. *Annual Review of Economics*, 17:721–746.

Amasino, D. R., Pace, D. D., and van der Weele, J. (2023). Self-serving bias in redistribution choices: Accounting for beliefs and norms. *Journal of Economic Psychology*, 98:102654.

Amasino, D. R., Pace, D. D., and van der Weele, J. J. (2024). Fair shares and selective attention. *American Economic Journal: Microeconomics*, 16(4):259–290.

Andre, P. (2025). Shallow meritocracy. *Review of Economic Studies*, 92(2):772–807.

Andrew, A., Bandiera, O., Costa Dias, M., and Landais, C. (2024). Women and men at work. *Oxford Open Economics*, 3(Supplement_1):i294–i322.

Andries, M., Bursztyn, L., Chaney, T., Djourelova, M., and Imas, A. (2026). In their shoes: Empathy through information. *The Quarterly Journal of Economics*, page qjag033.

Ashforth, B. E. and Mael, F. (1989). Social identity theory and the organization. *Academy of Management Review*, 14(1):20–39.

Babcock, L. and Loewenstein, G. (1997). Explaining bargaining impasse: The role of self-serving biases. *Journal of Economic Perspectives*, 11(1):109–126.

Balafoutas, L., Kocher, M. G., Putterman, L., and Sutter, M. (2013). Equality, equity and incentives: An experiment. *European Economic Review*, 60:32–51.

Baranski, A. and Muñoz-Herrera, M. (2024). The recency bias in the attribution of credit and blame for joint work outcomes. NYUAD Division of Social Science Working Paper 0099, New York University Abu Dhabi.

Becker, G. S. and Murphy, K. M. (1992). The division of labor, coordination costs, and knowledge. *The Quarterly Journal of Economics*, 107(4):1137–1160.

Benabou, R. and Tirole, J. (2006). Belief in a just world and redistributive politics. *The Quarterly Journal of Economics*, 121(2):699–746.

Bernstein, E. S. (2012). The transparency paradox: A role for privacy in organizational learning and operational control. *Administrative Science Quarterly*, 57(2):181–216.

Blau, P. (2017). *Exchange and power in social life*. Routledge.

Bloom, N. and Van Reenen, J. (2010). Why do management practices differ across firms and countries? *Journal of Economic Perspectives*, 24(1):203–224.

Bolton, P. and Dewatripont, M. (1994). The firm as a communication network. *The Quarterly Journal of Economics*, 109(4):809–839.

Breza, E., Kaur, S., and Shamdasani, Y. (2018). The morale effects of pay inequality. *The Quarterly Journal of Economics*, 133(2):611–663.

Buttner, E. H. and Lowe, K. B. (2017). Addressing internal stakeholders' concerns: The interactive effect of perceived pay equity and diversity climate on turnover intentions. *Journal of Business Ethics*, 143(3):621–633.

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.

Cappelen, A. W., Konow, J., Sørensen, E. Ø., and Tungodden, B. (2013a). Just luck: An experimental study of risk-taking and fairness. *American Economic Review*, 103(4):1398–1413.

Cappelen, A. W., Moene, K. O., Sørensen, E. Ø., and Tungodden, B. (2013b). Needs versus entitlements—an international fairness experiment. *Journal of the European Economic Association*, 11(3):574–598.

Cappelen, A. W., Sørensen, E. Ø., and Tungodden, B. (2010). Responsibility for what? Fairness and individual responsibility. *European Economic Review*, 54(3):429–441.

Cappelen, A. W. and Tungodden, B., editors (2019). *The Economics of Fairness*. Edward Elgar Publishing Limited.

Charness, G., Gneezy, U., and Henderson, A. (2018). Experimental methods: Measuring effort in economics experiments. *Journal of Economic Behavior & Organization*, 149:74–87.

Coutts, A., Gerhards, L., and Murad, Z. (2024). What to blame? Self-serving attribution bias with multi-dimensional uncertainty. *The Economic Journal*, 134(661):1835–1874.

Cullen, Z. and Perez-Truglia, R. (2022). How much does your boss make? The effects of salary comparisons. *Journal of Political Economy*, 130(3):766–822.

Durante, R., Putterman, L., and van der Weele, J. (2014). Preferences for redistribution and perception of fairness: An experimental study. *Journal of the European Economic Association*, 12(4):1059–1086.

Fehr, E. and Schmidt, K. M. (1999). A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics*, 114(3):817–868.

Fischbacher, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, 10(2):171–178.

Folbre, N., Gornick, J. C., Connolly, H., and Munzi, T. (2013). Women's employment, unpaid work, and economic inequality. In Gornick, J. C. and Jäntti, M., editors, *Income Inequality: Economic Disparities and the Middle Class in Affluent Countries*, pages 234–260. Stanford University Press, Stanford, CA.

Garicano, L. (2000). Hierarchies and the organization of knowledge in production. *Journal of Political Economy*, 108(5):874–904.

Gee, L. K., Migueis, M., and Parsa, S. (2017). Redistributive choices and increasing income inequality: experimental evidence for income as a signal of deservingness. *Experimental Economics*, 20(4):894–923.

Gesiarz, F., De Neve, J.-E., and Sharot, T. (2020). The motivational cost of inequality: Opportunity gaps reduce the willingness to work. *PLoS ONE*, 15(9):e0237914.

Gill, D. and Prowse, V. L. (2011). A novel computerized real effort task based on sliders. IZA Discussion Paper 5801, IZA.

Goldin, C. (1990). *Understanding the Gender Gap: An Economic History of American Women*. Oxford University Press.

Graeber, T., Roth, C., and Zimmermann, F. (2024). Stories, statistics, and memory. *The Quarterly Journal of Economics*, 139(4):2181–2225.

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, 15(8):534–539.

Holmström, B. and Milgrom, P. (1991). Multitask principal–agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, and Organization*, 7:24–52.

Isaksson, S. (2018). It takes two: Gender differences in group work. Working paper, available at SSRN.

Karagözoğlu, E. and Riedl, A. (2015). Performance information, production uncertainty, and subjective entitlements in bargaining. *Management Science*, 61(11):2611–2626.

Kinnl, K., Moeller, J., and Walter-Dockx, A. (2026). Borrowed plumes: the gender gap in claiming credit for teamwork. *Experimental Economics*, page 1–25.

Konow, J. (1996). A positive theory of economic fairness. *Journal of Economic Behavior & Organization*, 31(1):13–35.

Konow, J. (2000). Fair shares: Accountability and cognitive dissonance in allocation decisions. *American Economic Review*, 90(4):1072–1091.

Konow, J. (2003). Which is the fairest one of all? A positive analysis of justice theories. *Journal of Economic Literature*, 41(4):1188–1239.

Kwon, H. and Funaki, Y. (2023). The empathetic egoist: The effect of empathy on plural fairness ideals. *Available at SSRN 4441637*.

Lazear, E. P. (1989). Pay equality and industrial politics. *Journal of Political Economy*, 97(3):561–580.

Lekfuangfu, W. N., Powdthavee, N., and Riyanto, Y. E. (2023). Luck or rights? An experiment on preferences for redistribution following inheritance of opportunity. *Journal of Behavioral and Experimental Economics*, 106:102078.

Lezzi, E., Fleming, P., and Zizzo, D. J. (2015). Does it matter which effort task you use? A comparison of four effort tasks when agents compete for a prize. *SSRN Electronic Journal*.

Marks, M. A., Sabella, M. J., Burke, C. S., and Zaccaro, S. J. (2002). The impact of cross-training on team effectiveness. *Journal of Applied Psychology*, 87(1):3–13.

Mengel, F. and Weidenholzer, E. (2023). Preferences for redistribution. *Journal of Economic Surveys*, 37(5):1660–1677.

Mollerstrom, J., Reme, B.-A., and Sørensen, E. Ø. (2015). Luck, choice and responsibility—an experimental study of fairness views. *Journal of Public Economics*, 131:33–40.

Ozerturk, S. and Yildirim, H. (2025). Who gets the credit? Credit attribution, spillovers, and inefficiency in teams. *Games and Economic Behavior*, 154:246–266.

Pham, V., Jiang, L., and Kamijo, Y. (2026). When fairness is unfair: Norm abandonment in bargaining and its implications for peace negotiations. *Journal of Conflict Resolution*, 70(2-3):261–286.

Piketty, T. (1995). Social mobility and redistributive politics. *The Quarterly Journal of Economics*, 110(3):551–584.

Piketty, T. (2014). *Capital in the twenty-first century*. Harvard University Press.

Rayo, L. (2007). Relational incentives and moral hazard in teams. *The Review of Economic Studies*, 74(3):937–963.

Rodriguez-Lara, I. and Moreno-Garrido, L. (2012). Self-interest and fairness: self-serving choices of justice principles. *Experimental Economics*, 15:158–175.

Sarsons, H., Gërxhani, K., Reuben, E., and Schram, A. (2021). Gender differences in recognition for group work. *Journal of Political Economy*, 129(1):101–147.

Smulowitz, S. J. and Almandoz, J. (2021). Predicting employee wrongdoing: The complementary effect of CEO option pay and the pay gap. *Organizational Behavior and Human Decision Processes*, 162:123–135.

Thongpapanl, N., Kaciak, E., and Welsh, D. H. (2018). Growing and aging of entrepreneurial firms: Implications for job rotation and joint reward. *International Journal of Entrepreneurial Behavior & Research*, 24(6):1087–1103.

Todd, A. R. and Galinsky, A. D. (2014). Perspective-taking as a strategy for improving intergroup relations: Evidence, mechanisms, and qualifications. *Social and Personality Psychology Compass*, 8(7):374–387.

Ubeda, P. (2014). The consistency of fairness rules: An experimental study. *Journal of Economic Psychology*, 41:88–100.

Valero, V. (2022). Redistribution and beliefs about the source of income inequality. *Experimental Economics*, 25(3):876–901.

Weidmann, B., Vecci, J., Said, F., Bhalotra, S., Adhvaryu, A., Nyshadham, A., Tamayo, J., and Deming, D. (2026). How do you identify a good manager? *The Quarterly Journal of Economics*, 141(2):1581–1633.

Wiese, J. V., Powdthavee, N., Yeo, J. X. W., and Riyanto, Y. E. (2025). Unveiling the effects of hidden luck and merit on redistribution in groups. *Journal of Behavioral and Experimental Economics*, 117:102392.

Supplemental appendix to "Specialisation and the Allocation of Credit: Understanding and Appreciating Others' Work", Jun Hue and Jonathan Yeo

A Supplementary Analysis

Table A.1: Demographics of participants across treatments

	No Exp-No Info mean (sd)	No Exp-Info mean (sd)	Exp-No Info mean (sd)	Exp-Info mean (sd)
Gender				
Male	0.556	0.459	0.569	0.571
	(0.499)	(0.501)	(0.497)	(0.498)
Female	0.438	0.520	0.388	0.393
	(0.498)	(0.502)	(0.489)	(0.491)
Prefer not to say	0.007	0.020	0.043	0.036
	(0.083)	(0.142)	(0.204)	(0.187)
		Pearson χ^2*:* $p = 0.235$		
Academic Year				
1	0.451	0.367	0.517	0.452
	(0.499)	(0.485)	(0.502)	(0.501)
2	0.229	0.327	0.250	0.262
	(0.422)	(0.471)	(0.435)	(0.442)
3	0.153	0.184	0.103	0.143
	(0.361)	(0.389)	(0.306)	(0.352)
4	0.167	0.122	0.121	0.143
	(0.374)	(0.329)	(0.327)	(0.352)
Postgraduate	0.000	0.000	0.009	0.000
	(0.000)	(0.000)	(0.093)	(0.000)
		Pearson χ^2*:* $p = 0.496$		
Nationality				
Singaporean	0.542	0.602	0.509	0.417
	(0.500)	(0.492)	(0.502)	(0.496)
Malaysian	0.188	0.235	0.216	0.274
	(0.392)	(0.426)	(0.413)	(0.449)
Other Southeast Asian	0.104	0.031	0.138	0.167
	(0.307)	(0.173)	(0.346)	(0.375)
South Asian	0.111	0.051	0.043	0.036
	(0.315)	(0.221)	(0.204)	(0.187)
East Asian	0.056	0.082	0.095	0.107
	(0.230)	(0.275)	(0.294)	(0.311)
		Pearson χ^2*:* $p = 0.027$		

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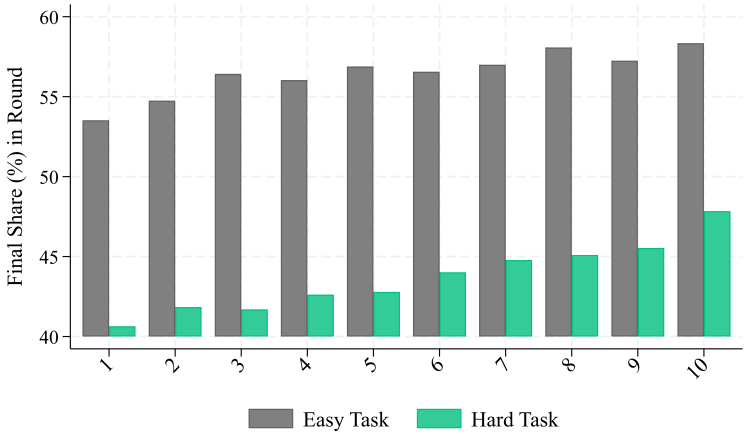
Table A.1 continued.

	No Exp-No Info mean (sd)	No Exp-Info mean (sd)	Exp-No Info mean (sd)	Exp-Info mean (sd)
School				
Nanyang Business School	0.132	0.143	0.138	0.250
	(0.340)	(0.352)	(0.346)	(0.436)
School of Chemistry, Chemical Engineering and Biotechnology	0.125	0.071	0.086	0.048
	(0.332)	(0.259)	(0.282)	(0.214)
School of Civil and Environmental Engineering	0.132	0.092	0.069	0.060
	(0.340)	(0.290)	(0.254)	(0.238)
School of Electrical and Electronic Engineering	0.139	0.163	0.112	0.155
	(0.347)	(0.372)	(0.317)	(0.364)
School of Mechanical and Aerospace Engineering	0.083	0.041	0.086	0.083
	(0.277)	(0.199)	(0.282)	(0.278)
School of Materials Science and Engineering	0.000	0.010	0.000	0.036
	(0.000)	(0.101)	(0.000)	(0.187)
College of Computing and Data Science	0.104	0.092	0.112	0.143
	(0.307)	(0.290)	(0.317)	(0.352)
School of Biological Sciences	0.042	0.041	0.069	0.012
	(0.201)	(0.199)	(0.254)	(0.109)
School of Physical and Mathematical Sciences	0.021	0.071	0.138	0.071
	(0.143)	(0.259)	(0.346)	(0.259)
School of Social Sciences	0.160	0.184	0.147	0.083
	(0.368)	(0.389)	(0.355)	(0.278)
School of Humanities	0.042	0.082	0.034	0.060
	(0.201)	(0.275)	(0.183)	(0.238)
Art, Design and Media	0.014	0.000	0.000	0.000
	(0.117)	(0.000)	(0.000)	(0.000)
School of Communications	0.007	0.000	0.000	0.000
	(0.083)	(0.000)	(0.000)	(0.000)
National Institute of Education	0.000	0.010	0.009	0.000
	(0.000)	(0.101)	(0.093)	(0.000)
		Pearson χ^2*:* $p = 0.029$		
Observations	144	98	116	84

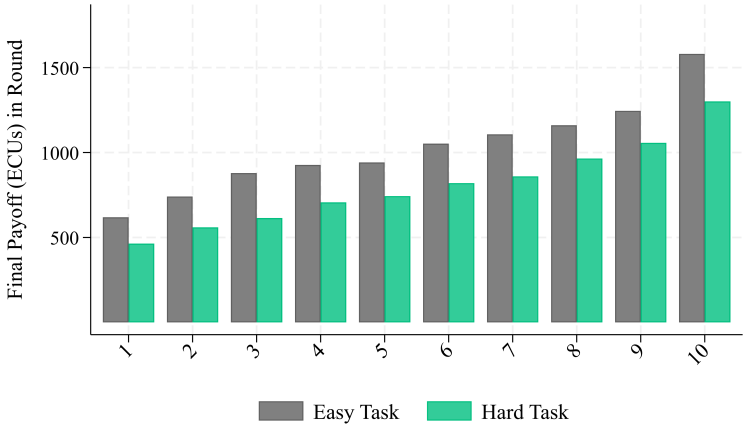
Notes: Entries report means, with standard deviations in parentheses, by treatment condition. Pearson χ^2 tests assess whether the distribution of each categorical characteristic differs across the four treatment conditions. The χ^2 tests should be interpreted cautiously where categories contain small cell counts. Ethnicity is not reported because of substantial noise in participants' responses.

Figure A.1: Inequality between Easy and Hard Taskers

(a) Mean share by score decile



(b) Mean earnings by score decile



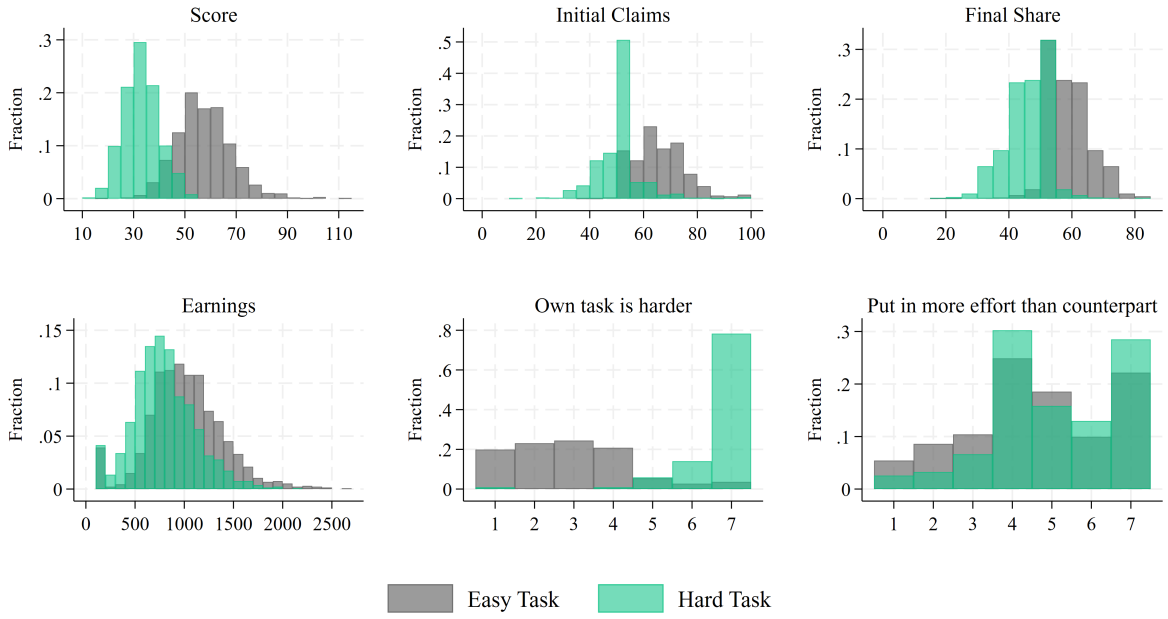
Notes: Bars report means calculated from individual-round observations. Score deciles are constructed separately for easy and hard taskers using their own individual scores. Panel (a) reports final shares and excludes pairs that did not reach agreement, representing 3.9% of pair-rounds. Panel (b) reports earnings and includes all pair-rounds.

Table A.2: Descriptive statistics by task profession

	Grid	**Slider**	**Difference**
Panel A: Outcomes	*mean (sd)*	*mean (sd)*	*b (se)*
Individual Score	44.544	44.860	-0.315
	(16.961)	(13.195)	(6.036)
Initial Claim	54.038	57.730	-3.692
	(11.213)	(12.323)	(3.728)
Final Share	48.506	51.494	-2.988
	(9.498)	(9.498)	(3.212)
Earnings	887.344	919.520	-32.176
	(398.675)	(342.512)	(56.295)
"Own task is harder"	4.792	4.783	0.009
	(2.283)	(2.188)	(0.937)
"Put in more effort than counterpart"	4.443	4.765	-0.321*
	(1.733)	(1.618)	(0.146)
Panel B: Responsiveness of Initial Claims to Score Ratio (Grid Score/Slider Score)	*b (se)*	*b (se)*	*b (se)*
$\beta_{ScoreRatio}$	10.051***	-9.689***	
	(0.861)	(1.194)	
$\lvert\beta_{ScoreRatio}\rvert$	10.051***	9.689***	0.363
	(0.861)	(1.194)	(1.250)

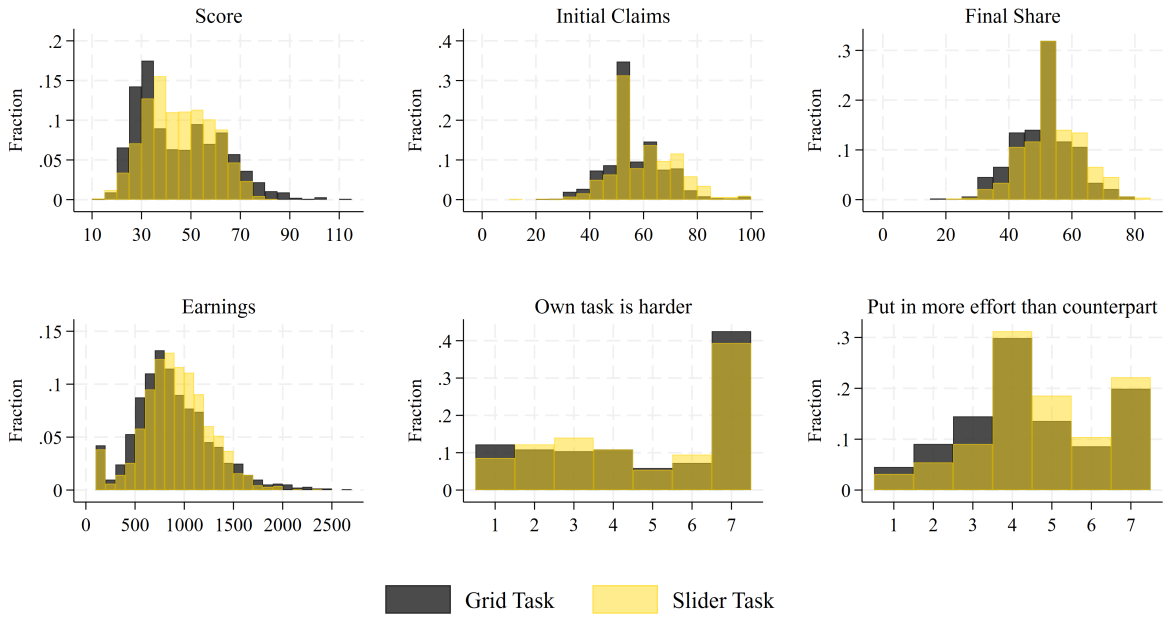
Notes: Panel A reports means, with standard deviations in parentheses, separately for Grid and Slider taskers. Individual Score, Initial Claim, Final Share, and Earnings use individual-round observations; the two survey outcomes use individual-level observations and are measured on seven-point scales. Final Share excludes pairs that did not reach agreement. Tests of differences use session clustered standard errors. Panel B reports coefficients from a session random-effects regression allowing separate intercepts and score-ratio slopes for Grid and Slider taskers. The score ratio is the Grid tasker's score divided by the Slider tasker's score. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.2: Distribution of outcomes by task difficulty



Notes: Histograms show distributions separately for easy and hard taskers. Individual Score, Initial Claim, Final Share, and Earnings use individual-round observations; "Own task is harder" and "Put in more effort than counterpart" use individual-level survey responses measured on seven-point scales. Final Share excludes pairs that did not reach agreement.

Figure A.3: Distribution of outcomes by task profession



Notes: Histograms show distributions separately for Grid and Slider taskers. Individual Score, Initial Claim, Final Share, and Earnings use individual-round observations; "Own task is harder" and "Put in more effort than counterpart" use individual-level survey responses measured on seven-point scales. Final Share excludes pairs that did not reach agreement.

Table A.3: Treatment effects on initial claims and final share

Dep Var:	Initial Claims		Final Share
	Easy Taskers (1)	Hard Taskers (2)	Easy (3)
Exposure	-2.332**	1.391	-1.520*
	(1.032)	(0.895)	(0.778)
Info	0.699	0.222	-0.013
	(1.042)	(0.990)	(0.807)
Score Ratio (Quantile 1)	-6.051***	3.889***	-5.769***
	(1.284)	(0.728)	(0.787)
Score Ratio (Quantile 2)	-1.403**	0.741	-1.918***
	(0.588)	(0.660)	(0.617)
Score Ratio (Quantile 3)	-0.002	0.676	-1.596***
	(1.026)	(0.933)	(0.409)
Score Ratio (Quantile 5)	2.560***	-1.316	1.880***
	(0.789)	(0.983)	(0.687)
Score Ratio (Quantile 6)	3.789**	-0.988	1.775**
	(1.482)	(0.859)	(0.849)
Score Ratio (Quantile 7)	5.326***	-1.453	2.747**
	(1.407)	(1.254)	(1.233)
Constant	62.075***	46.742***	56.446***
	(2.351)	(1.496)	(1.479)
Joint Earnings	✓	✓	✓
Round, Task, Exchange Rate FE	✓	✓	✓
Observations	1326	1326	1275

Notes: Session random-effects regressions using individual-round observations. The score ratio is the easy tasker's score divided by the hard tasker's score and is divided into seven quantiles; quantile 4 is the omitted category. All specifications include round, task, and exchange-rate fixed effects and control for joint earnings. Column (3) includes only pairs that reached agreement and reports the final share received by the easy tasker. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Marginal effects on initial claims and final share, by score-ratio quantile

Dep Var:	Initial Claims		Final Share
	Easy Taskers (1)	Hard Taskers (2)	Easy (3)
Score Ratio (Quantile 1)	-7.675***	3.858***	-5.389***
	(1.368)	(0.769)	(0.882)
Score Ratio (Quantile 2)	-2.433***	1.062	-1.670**
	(0.784)	(0.713)	(0.811)
Score Ratio (Quantile 3)	-0.611	3.014**	-2.184***
	(1.199)	(1.439)	(0.730)
Score Ratio (Quantile 5)	1.364	-0.410	1.463
	(1.127)	(1.046)	(0.942)
Score Ratio (Quantile 6)	1.982	1.563*	0.268
	(1.874)	(0.933)	(1.518)
Score Ratio (Quantile 7)	1.565	1.252	-0.235
	(1.233)	(1.277)	(1.226)
Exposure × Score Ratio (Quantile 1)	-2.185	2.895***	-2.240***
	(1.775)	(0.903)	(0.602)
Exposure × Score Ratio (Quantile 2)	-2.296*	2.455**	-2.096**
	(1.291)	(1.001)	(0.924)
Exposure × Score Ratio (Quantile 3)	-4.331**	-0.600	-1.851
	(2.123)	(1.413)	(1.206)
Exposure × Score Ratio (Quantile 4)	-3.404**	2.804**	-1.763
	(1.709)	(1.223)	(1.330)
Exposure × Score Ratio (Quantile 5)	-2.168*	1.818	-1.438
	(1.217)	(2.012)	(1.145)
Exposure × Score Ratio (Quantile 6)	-1.181	-0.804	-0.257
	(1.746)	(1.245)	(1.176)
Exposure × Score Ratio (Quantile 7)	0.291	0.643	0.002
	(1.381)	(2.404)	(1.856)
Info × Score Ratio (Quantile 1)	1.532	1.540*	-1.318*
	(2.257)	(0.835)	(0.743)
Info × Score Ratio (Quantile 2)	-0.282	1.242	-1.435*
	(1.390)	(0.957)	(0.762)
Info × Score Ratio (Quantile 3)	0.620	-0.243	-0.111
	(2.112)	(1.098)	(1.066)
Info × Score Ratio (Quantile 4)	-0.988	1.527	-1.042
	(1.796)	(1.350)	(1.388)
Info × Score Ratio (Quantile 5)	-0.255	0.130	-0.544
	(1.177)	(1.970)	(1.095)
Info × Score Ratio (Quantile 6)	0.669	-0.405	0.573
	(1.718)	(1.363)	(1.114)
Info × Score Ratio (Quantile 7)	3.517**	-2.566	3.785**
	(1.635)	(2.369)	(1.842)
Constant	63.807***	45.029***	57.457***
	(2.315)	(1.553)	(1.539)
Joint earnings	✓	✓	✓
Task, round, and exchange-rate fixed effects	✓	✓	✓
Observations	1326	1326	1275

Notes: Session random-effects regressions using individual-round observations. The score ratio is the easy tasker's score divided by the hard tasker's score and is divided into seven quantiles. All specifications include round, task, and exchange-rate fixed effects and control for joint earnings. Column (3) includes only pairs that reached agreement and reports the final share received by the easy tasker. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Treatment effects on initial claims by round

Dep Var:	Initial Claims	
	Easy Taskers	Hard Taskers
	(1)	(2)
Exposure × Round 1	-1.985*	1.107
	(1.064)	(1.014)
Exposure × Round 2	-2.449*	1.142
	(1.319)	(1.129)
Exposure × Round 3	-3.199***	1.933*
	(1.242)	(1.062)
Exposure × Round 4	-2.534**	0.826
	(1.234)	(0.907)
Exposure × Round 5	-2.682**	1.616
	(1.322)	(1.099)
Exposure × Round 6	-1.136	1.719
	(1.263)	(1.525)
Information × Round 1	-0.255	0.116
	(1.128)	(1.123)
Information × Round 2	1.203	0.652
	(1.449)	(1.150)
Information × Round 3	1.445	0.268
	(1.254)	(1.125)
Information × Round 4	1.019	0.271
	(1.190)	(0.973)
Information × Round 5	0.084	-0.177
	(1.321)	(1.206)
Information × Round 6	0.706	0.205
	(1.175)	(1.537)
Joint Earnings	✓	✓
Round, Task, Exchange Rate Fixed effects	✓	✓
Score Ratio Fixed effects	✓	✓
Observations	1326	1326

Notes: Session random-effects regressions using individual-round observations. The score ratio is the easy tasker's score divided by the hard tasker's score and is divided into seven quantiles. All specifications include round, task, exchange-rate, Score Ratio fixed effects and control for joint earnings. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: FMM estimates using initial claims

Treatment:	No Exp No Info	No Exp Info	Exp No Info	Exp Info
Proportion of:		**Easy Taskers**		
Equal	0.125**	0.063	0.137**	0.204**
	(0.051)	(0.060)	(0.070)	(0.086)
Surface-level	0.744***	0.744***	0.588***	0.613***
	(0.058)	(0.067)	(0.072)	(0.083)
Weighted	0.131**	0.194**	0.275***	0.183**
	(0.054)	(0.077)	(0.077)	(0.088)
Proportion of:		**Hard Taskers**		
Equal	0.501***	0.537***	0.615***	0.239**
	(0.079)	(0.109)	(0.082)	(0.102)
Surface-level	0.330***	0.215***	0.291***	0.186***
	(0.058)	(0.070)	(0.065)	(0.062)
Weighted	0.169**	0.248**	0.094	0.575***
	(0.070)	(0.103)	(0.072)	(0.111)
β		34.305*** (2.538)		
σ		125.506*** (1.822)		

Notes: The table reports estimated probabilities of the egalitarian, surface-level-meritocratic, and weighted-meritocratic types separately by role and treatment cell. Types are estimated at the individual level using each participant's six initial claims, and estimated probabilities sum to one within each role-treatment cell. The parameters β and σ are constrained to be common across treatments, task roles, and fairness types. Delta-method standard errors are reported in parentheses. Appendix C describes the estimation procedure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Regression-like estimates from Classification — FMM

Proportion of:	Egalitarian	**Easy Task** Surface-level	Weighted
Exposure	0.077	-0.143**	0.067
	(0.067)	(0.070)	(0.075)
Information	0.003	0.012	-0.015
	(0.067)	(0.070)	(0.075)
Constant	0.092*	0.738***	0.170***
	(0.050)	(0.055)	(0.053)
Proportion of:	Egalitarian	**Hard Task** Surface-level	Weighted
Exposure	-0.092	-0.034	0.126
	(0.093)	(0.063)	(0.090)
Information	-0.170*	-0.110*	0.280***
	(0.093)	(0.063)	(0.090)
Constant	0.604***	0.328***	0.068
	(0.073)	(0.053)	(0.067)

Notes: Entries report average changes in the estimated probability of each fairness type. Estimates are linear combinations of those reported in Table A.6. The Exposure effect is $\frac{1}{2}[(p_3 - p_1) + (p_4 - p_2)]$, and the Information effect is $\frac{1}{2}[(p_2 - p_1) + (p_4 - p_3)]$, where p_c denotes the estimated probability in cell c: 1 = No Exposure/No Information, 2 = No Exposure/Information, 3 = Exposure/No Information, and 4 = Exposure/Information. Delta-method standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Potential mechanisms

Dep Var:	Could have done better than counterpart	Put in more effort than counterpart	Own task is harder	Did not understand other's task	My task should earn more	Affected by past allocations	Hard to agree	Cooperation needed	Closeness to counterpart	Ingroup − Outgroup Closeness	Closeness between professions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						Easy Taskers					
Exposure	0.018	-0.269	-0.495***	-0.652***	-0.751***	-0.361	-0.048	-0.225	0.224*	-0.471**	0.134
	(0.225)	(0.206)	(0.183)	(0.169)	(0.251)	(0.308)	(0.187)	(0.312)	(0.128)	(0.219)	(0.223)
Info	0.055	-0.020	-0.117	0.013	-0.090	0.117	-0.146	0.288	-0.028	0.059	0.030
	(0.250)	(0.213)	(0.208)	(0.143)	(0.293)	(0.321)	(0.192)	(0.326)	(0.174)	(0.289)	(0.229)
Constant	4.717***	4.401***	4.082***	2.114***	3.796***	5.757***	5.193***	8.307***	3.592***	2.081***	4.104***
	(0.345)	(0.389)	(0.409)	(0.403)	(0.713)	(1.073)	(0.650)	(1.161)	(0.467)	(0.749)	(0.801)
						Hard Taskers					
Exposure	0.004	-0.240	-0.115	-0.880***	-0.152	0.044	-0.345*	0.443	-0.028	-0.488	-0.074
	(0.180)	(0.159)	(0.087)	(0.143)	(0.203)	(0.320)	(0.199)	(0.360)	(0.222)	(0.334)	(0.177)
Info	-0.126	-0.287	0.010	0.006	-0.191	0.480	0.438**	-1.027***	-0.295	-0.699**	-0.381*
	(0.204)	(0.186)	(0.094)	(0.152)	(0.229)	(0.342)	(0.200)	(0.343)	(0.233)	(0.312)	(0.206)
Constant	5.776***	5.371***	6.061***	2.921***	4.706***	3.589***	4.143***	7.811***	0.790	1.927	2.312**
	(0.241)	(0.230)	(0.314)	(0.419)	(1.167)	(1.209)	(0.823)	(1.603)	(0.731)	(1.722)	(1.112)
Observations	1326	1326	221	221	221	221	221	221	221	221	221

Notes: Session random effects regressions estimated separately for easy and hard taskers. Columns (1)–(2) use individual-round responses; Columns (3)–(11) use individual-level post-experiment responses. Higher values indicate greater agreement or greater perceived cooperation/closeness, as applicable; Column (10) is closeness to one's own profession minus closeness to the other profession. Columns (1)–(2) include round, task, exchange-rate, and score-ratio-quantile fixed effects and control for joint earnings. Columns (3)–(11) include task and exchange-rate fixed effects and control for mean joint earnings and mean score-ratio quantile. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Controlling for task understanding, closeness and perceived deservingness

Dep Var:	Initial Claims					
	Easy			Hard		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	-2.169**	-2.037**	-1.596	1.403	1.431	1.407
	(1.044)	(1.027)	(0.998)	(0.973)	(0.909)	(0.904)
Info	0.789	0.679	0.773	0.225	0.218	0.232
	(0.962)	(1.080)	(0.948)	(1.028)	(0.990)	(0.995)
Own task is harder	1.001***			-0.949		
	(0.262)			(1.294)		
Did not understand other's task	-0.555			0.078		
	(0.388)			(0.299)		
IOS		-1.283***			-0.266	
		(0.339)			(0.314)	
Ingroup − Outgroup Closeness		-0.165			0.084	
		(0.195)			(0.161)	
My task should earn more			0.943**			0.053
			(0.378)			(0.316)
Constant	59.394***	66.840***	57.636***	52.903***	47.083***	46.469***
	(2.359)	(2.905)	(2.923)	(9.238)	(1.606)	(2.709)
Joint Earnings	✓	✓	✓	✓	✓	✓
Round, Task, Exchange Rate Fixed effects	✓	✓	✓	✓	✓	✓
Score ratio Fixed effects	✓	✓	✓	✓	✓	✓
Observations	1326	1326	1326	1326	1326	1326

Notes: Session random-effects regressions using individual-round observations. All specifications include round, task, exchange-rate and score ratio quantile fixed effects and control for joint earnings. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Treatment effects on bargaining time and number of bargaining rounds

	Bargain Time(s) (1)	No. of Bargaining Rounds (2)
Exposure	-12.898	-8.684***
	(8.407)	(2.867)
Info	5.550	-0.215
	(8.852)	(3.150)
Constant	68.517***	5.138
	(18.950)	(7.538)
Round, Task, Exchange Rate, Score Ratio Fixed effects	✓	✓
Joint Earnings	✓	✓
Observations	1275	1275

Notes: Session random-effects regressions using pair-round observations for pairs that reached agreement. Column (1) measures total bargaining duration in seconds; Column (2) measures the number of bargaining rounds required to reach agreement. The score ratio is the easy tasker's score divided by the hard tasker's score and is divided into seven quantiles. All specifications include round, task, exchange-rate, and score-ratio-quantile fixed effects and control for joint earnings. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Exposure, Information and claim adjustments

Dep Var:	*Claim of Easy Tasker Strictly Decreases*	*Claim of Hard Tasker Strictly increases*
	when $Claim_{easy} - Claim_{hard}$ in past bargaining round ≥ 0	
Exposure	0.015**	0.002
	(0.006)	(0.004)
Info	-0.000	0.003
	(0.007)	(0.005)
Constant	0.135***	0.031***
	(0.022)	(0.009)
Joint Earnings	✓	✓
Round, Task, Exchange Rate Fixed effects	✓	✓
Score Ratio Fixed effects	✓	✓
Observations	38768	38774

Notes: Linear-probability session random-effects regressions using bargaining-round observations. The dependent variables indicate whether the easy tasker strictly decreases their claim or the hard tasker strictly increases their claim in the current bargaining round. The sample is restricted to observations for which the easy tasker's claim in the preceding bargaining round was at least as large as the hard tasker's; these account for 89.4% of bargaining-round observations with a preceding pair of claims. Sample sizes differ slightly because, in some pairs that did not reach agreement, only one participant submitted a final claim. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Treatment effects on productivity over time

Dep Var:	Standardised Score in Task			
	Easy		Hard	
	(1)	(2)	(3)	(4)
Exposure	0.043	0.022	0.088	0.122
	(0.123)	(0.057)	(0.155)	(0.116)
Info	0.105	0.001	0.128	0.011
	(0.137)	(0.061)	(0.181)	(0.125)
Period	0.192***	0.192***	0.152***	0.152***
	(0.013)	(0.013)	(0.031)	(0.031)
Exposure × Period	0.037**	0.037**	-0.006	-0.006
	(0.015)	(0.015)	(0.039)	(0.039)
Info × Period	-0.009	-0.009	-0.009	-0.009
	(0.017)	(0.017)	(0.041)	(0.041)
Score in Training round		0.044***		0.066***
		(0.004)		(0.005)
Standardised Warm-Up Score		0.183***		0.142***
		(0.038)		(0.033)
Constant	-0.411**	-3.242***	-0.744***	-3.066***
	(0.193)	(0.252)	(0.167)	(0.260)
Task, Exchange Rate Fixed Effects	✓	✓	✓	✓
Observations	1326	1326	1326	1326

Notes: Session random-effects regressions using individual-round observations. The dependent variable is the production score standardised within each task difficulty. Round is normalised so that production Round 1 equals zero. Performance in the training and scores on the warm-up task (standardised within each unique task) are used as ability controls. All specifications include task and exchange-rate fixed effects. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Robustness Checks

Table B.1: Treatment effects on initial claims and final share (demographic controls)

Dep Var:	Initial Claim		Final Share
	Easy	Hard	Easy
	(1)	(2)	(3)
Exposure	-2.256***	1.093	-1.390**
	(0.837)	(0.868)	(0.602)
Info	1.305	0.038	0.184
	(0.920)	(0.771)	(0.675)
Score Ratio (Quantile 1)	-5.915***	3.229***	-5.229***
	(1.319)	(0.752)	(0.815)
Score Ratio (Quantile 2)	-1.355**	0.464	-1.817***
	(0.670)	(0.665)	(0.607)
Score Ratio (Quantile 3)	-0.142	0.610	-1.546***
	(0.855)	(0.911)	(0.480)
Score Ratio (Quantile 5)	3.118***	-1.509	2.184***
	(0.738)	(0.947)	(0.711)
Score Ratio (Quantile 6)	4.200***	-0.723	1.834**
	(1.354)	(0.787)	(0.881)
Score Ratio (Quantile 7)	5.620***	-1.157	2.670**
	(1.187)	(1.225)	(1.270)
Constant	59.445***	48.486***	56.139***
	(2.492)	(2.269)	(1.492)
Joint Earnings	✓	✓	✓
Round, Task, Exchange Rate Fixed effects	✓	✓	✓
Gender, Academic Year, School, Nationality Fixed effects	✓	✓	✓
Observations	1326	1326	1275

Notes: Session random-effects regressions using individual-round observations. The score ratio is the easy tasker's score divided by the hard tasker's score and is divided into seven quantiles; quantile 4 is the omitted category. Specifications are those in Table A.3, controlling in addition for gender, academic year, school and nationality. Column (3) includes only pairs that reached agreement and reports the final share received by the easy tasker. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Marginal effects on initial claims and final share, by score-ratio quantile (demographic controls)

Dep Var:	Initial Claim		Final Share
	Easy	Hard	Easy
	(1)	(2)	(3)
Score Ratio (Quantile 1)	-8.132***	3.062***	-5.319***
	(1.194)	(0.985)	(0.857)
Score Ratio (Quantile 2)	-2.963***	0.813	-1.879**
	(0.970)	(0.752)	(0.755)
Score Ratio (Quantile 3)	-0.737	2.563*	-2.119***
	(0.857)	(1.349)	(0.737)
Score Ratio (Quantile 4)	0.000	0.000	0.000
	(.)	(.)	(.)
Score Ratio (Quantile 5)	1.795*	-0.656	1.542*
	(1.056)	(0.990)	(0.888)
Score Ratio (Quantile 6)	2.101	1.457*	0.153
	(1.668)	(0.846)	(1.438)
Score Ratio (Quantile 7)	2.312*	1.350	-0.009
	(1.275)	(1.316)	(1.244)
Exposure × Score Ratio (Quantile 1)	-1.868	2.978***	-2.274***
	(1.781)	(0.756)	(0.817)
Exposure × Score Ratio (Quantile 2)	-1.758	1.258	-1.936**
	(1.353)	(1.136)	(0.858)
Exposure × Score Ratio (Quantile 3)	-4.789***	-0.546	-2.116**
	(1.564)	(1.353)	(0.995)
Exposure × Score Ratio (Quantile 4)	-3.971***	2.473*	-2.007*
	(1.452)	(1.299)	(1.169)
Exposure × Score Ratio (Quantile 5)	-1.509	1.793	-1.129
	(1.167)	(2.010)	(1.129)
Exposure × Score Ratio (Quantile 6)	-1.356	-0.314	-0.201
	(1.654)	(1.236)	(1.033)
Exposure × Score Ratio (Quantile 7)	-0.276	0.218	-0.232
	(1.285)	(1.988)	(1.760)
Info × Score Ratio (Quantile 1)	2.467	1.329	-0.837
	(2.535)	(0.959)	(0.943)
Info × Score Ratio (Quantile 2)	0.774	1.784*	-1.194*
	(1.228)	(0.980)	(0.662)
Info × Score Ratio (Quantile 3)	1.472	-0.364	0.303
	(1.548)	(1.209)	(0.877)
Info × Score Ratio (Quantile 4)	-0.299	0.954	-0.944
	(1.571)	(1.174)	(1.333)
Info × Score Ratio (Quantile 5)	-0.237	-0.148	-0.647
	(1.067)	(1.770)	(1.101)
Info × Score Ratio (Quantile 6)	1.452	-0.817	0.790
	(1.657)	(1.237)	(0.949)
Info × Score Ratio (Quantile 7)	3.568**	-2.638	3.770**
	(1.388)	(2.108)	(1.799)
Constant	61.076***	47.325***	57.065***
	(2.571)	(2.333)	(1.400)
Joint Earnings	✓	✓	✓
Round, Task, Exchange Rate Fixed effects	✓	✓	✓
Gender, Academic Year, School, Nationality Fixed effects	✓	✓	✓
Observations	1326	1326	1275

Notes: Session random-effects regressions using individual-round observations. The score ratio is the easy tasker's score divided by the hard tasker's score and is divided into seven quantiles; quantile 4 is the omitted category. Specifications are those in Table A.4, controlling in addition for gender, academic year, school and nationality. Column (3) includes only pairs that reached agreement and reports the final share received by the easy tasker. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Robustness of different specifications

	Session RE Session clustered SE (1)	OLS Two-way clustered SE (2)	OLS Session clustered SE (3)	OLS Session wild-cluster BS (4)
Panel A: Dep Var: Initial Claims (Easy)				
Exposure	-2.332**	-2.190**	-2.190**	$p = 0.068$
	(1.032)	(1.004)	(0.986)	
Information	0.699	0.703	0.703	$p = 0.541$
	(1.042)	(1.147)	(0.995)	
Joint Earnings	✓	✓	✓	
Round, Task, Exchange Rate Fixed effects	✓	✓	✓	
Score Ratio Fixed effects	✓	✓	✓	
Panel B: Dep Var: Initial Claims (Hard)				
Exposure	1.391	1.273	1.273	$p = 0.187$
	(0.895)	(0.968)	(0.876)	
Information	0.222	0.205	0.205	$p = 0.863$
	(0.990)	(0.943)	(0.955)	
Joint Earnings	✓	✓	✓	
Round, Task, Exchange Rate Fixed effects	✓	✓	✓	
Score Ratio Fixed effects	✓	✓	✓	
Panel C: Dep Var: Final Share (Easy)				
Exposure	-1.520*	-1.345*	-1.345*	$p = 0.102$
	(0.778)	(0.712)	(0.733)	
Information	-0.013	-0.019	-0.019	$p = 0.992$
	(0.807)	(0.757)	(0.751)	
Joint Earnings	✓	✓	✓	
Round, Task, Exchange Rate Fixed effects	✓	✓	✓	
Score Ratio Fixed effects	✓	✓	✓	
Panel D: Dep Var: No. of Bargaining Rounds				
Exposure	-8.684***	-8.795*	-8.795***	$p = 0.013$
	(2.867)	(4.945)	(2.894)	
Information	-0.215	0.274	0.274	$p = 0.934$
	(3.150)	(5.456)	(3.026)	
Joint Earnings	✓	✓	✓	
Round, Task, Exchange Rate Fixed effects	✓	✓	✓	
Score Ratio Fixed effects	✓	✓	✓	
Panel E: Dep Var: Standardised Score in Task (Easy)				
Exposure × Round	0.037**	0.037***	0.037**	$p = 0.039$
	(0.015)	(0.013)	(0.015)	
Information × Round	-0.009	-0.009	-0.009	$p = 0.616$
	(0.017)	(0.013)	(0.017)	
Task, Exchange Rate Fixed Effects	✓	✓	✓	
Ability controls	✓	✓	✓	

Notes: Columns (1)–(3) report estimates from the same specifications under alternative estimators and inference procedures. Column (1) reports session random-effects estimates with standard errors clustered at the session level; Column (2) reports OLS estimates with two-way clustering by easy- and hard-tasker identifiers; Column (3) reports OLS estimates with standard errors clustered at the session level. Column (4) reports wild-cluster-bootstrap p-values based on the OLS specification in Column (3), clustering at the session level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Treatment effects on initial claims and final share (with interaction)

Dep Var:	Initial Claim		Final Share
	Easy	Hard	Easy
	(1)	(2)	(3)
Exposure	-1.495	1.966	-1.537
	(1.526)	(1.220)	(1.074)
Info	1.666	0.861	-0.235
	(1.211)	(1.217)	(0.994)
Exposure × Info	-2.131	-1.395	0.467
	(1.599)	(1.752)	(1.332)
Score Ratio (Quantile 1)	-6.060***	3.905***	-5.592***
	(1.285)	(0.737)	(0.766)
Score Ratio (Quantile 2)	-1.394**	0.776	-1.879***
	(0.589)	(0.672)	(0.614)
Score Ratio (Quantile 3)	-0.004	0.666	-1.747***
	(1.026)	(0.924)	(0.430)
Score Ratio (Quantile 5)	2.576***	-1.262	1.874**
	(0.788)	(0.999)	(0.736)
Score Ratio (Quantile 6)	3.791**	-0.970	1.740**
	(1.481)	(0.858)	(0.857)
Score Ratio (Quantile 7)	5.347***	-1.437	2.446*
	(1.409)	(1.260)	(1.291)
Constant	61.541***	46.508***	56.984***
	(2.354)	(1.519)	(1.530)
Round, Task, Exchange Rate Fixed effects	✓	✓	✓
Joint Earnings	✓	✓	✓
Observations	1326	1326	1275

Notes: Session random-effects regressions using individual-round observations. The score ratio is the easy tasker's score divided by the hard tasker's score and is divided into seven quantiles; quantile 4 is the omitted category. All specifications include round, task, and exchange-rate fixed effects and control for joint earnings. Column (3) includes only pairs that reached agreement and reports the final share received by the easy tasker. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Finite Mixture Model Estimation

Following Cappelen et al. (2010), we estimate the prevalence of three fairness types: (i) strict egalitarians, (ii) surface-level meritocrats, and (iii) weighted meritocrats, for each role-treatment cell. The perceived fair allocations for each fairness type are as follows:

1. Strict Egalitarians (SE): $m_i^{SE}(\mathbf{q}) = \frac{V(\mathbf{q})}{2}$
2. Surface-level Meritocrats (SM): $m_i^{SM}(\mathbf{q}) = \frac{q_i}{q_1+q_2}V(\mathbf{q})$
3. Weighted Meritocrats (WM): $m_i^{WM}(\mathbf{q}) = \frac{q_i/\bar{q}_i}{q_1/\bar{q}_1+q_2/\bar{q}_2}V(\mathbf{q})$

Surface-level Meritocrats correspond to workers in our model who completely ignore the circumstances of different task difficulties. Weighted Meritocrats instead completely account for the different task difficulties.[1] Strict egalitarians are workers who feel that joint output should be distributed equally no matter what.

We allow the prevalence of the three fairness types to vary jointly by treatment and task role. Let the indexes for the four treatments be:

$$t \in \mathcal{T} = \left\{ \begin{array}{l} \text{No Exposure, No Information;} \\ \text{No Exposure, Information;} \\ \text{Exposure, No Information;} \\ \text{Exposure, Information} \end{array} \right\}$$

Furthermore, let the index of the worker's assigned task role be:

$$d \in \mathcal{D} = \{\text{Easy}, \text{Hard}\}$$

For each treatment–role cell, define

$$\mathbf{p}_{td} = \left(p_{td}^{SE}, p_{td}^{SM}, p_{td}^{WM}\right),$$

where $p_{td}^{SE} + p_{td}^{SM} + p_{td}^{WM} = 1,\ p_{td}^{k} \geq 0$ for all $k \in \{SE, SM, WM\}$.

[1] For weighted meritocrats, $\bar{q}_i$ is the pilot-session average for the relevant task variant in Figure 1, Panel B.

For each fairness type $k \in \{SE, SM, WM\}$, we assume that the initial claim (in ECUs) made by individual i in round r satisfies:

$$y_{ir} = \frac{V(\mathbf{q}_r)}{\beta} + m_i^k(\mathbf{q}_r) + \epsilon_{ir},$$

where $\epsilon_{ir} \overset{\text{iid}}{\sim} \mathcal{N}(0, \sigma^2)$.

The parameters β and σ are common across treatments, task roles, and fairness types. This restriction simplifies estimation and ensures that differences in the estimated mixing proportions are not mechanically driven by treatment- or role-specific error variances.

Conditional on fairness type k, the round-level density is

$$f(y_{ir} \mid k; \beta, \sigma) = \frac{1}{\sigma}\phi\left(\frac{y_{ir} - V(\mathbf{q}_r)/\beta - m_i^k(\mathbf{q}_r)}{\sigma}\right),$$

where $\phi(\cdot)$ denotes the standard normal density. Following this, the likelihood contribution from an individual in treatment t and role d is:

$$\begin{aligned} f\left(\mathbf{y}_i; \beta, \sigma, \mathbf{p}_{td}\right) = p_{td}^{SE} \prod_{r=1}^{6} f(y_{ir} \mid SE; \beta, \sigma) \\ + p_{td}^{SM} \prod_{r=1}^{6} f(y_{ir} \mid SM; \beta, \sigma) \\ + p_{td}^{WM} \prod_{r=1}^{6} f(y_{ir} \mid WM; \beta, \sigma), \end{aligned}$$

where $\mathbf{y}_i = (y_{i1}, \ldots, y_{i6})$ denotes individual i's sequence of initial claims.

We then maximize the full sample log likelihood:

$$\mathcal{L} = \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{D}} \sum_{i \in (t,d)} \log f\left(\mathbf{y}_i; \beta, \sigma, \mathbf{p}_{td}\right),$$

with respect to the eight treatment–role-specific mixing distributions, $\{\mathbf{p}_{td} : t \in \mathcal{T},\ d \in \mathcal{D}\}$, and the common parameters β and σ.

D Minimum Distance Classification

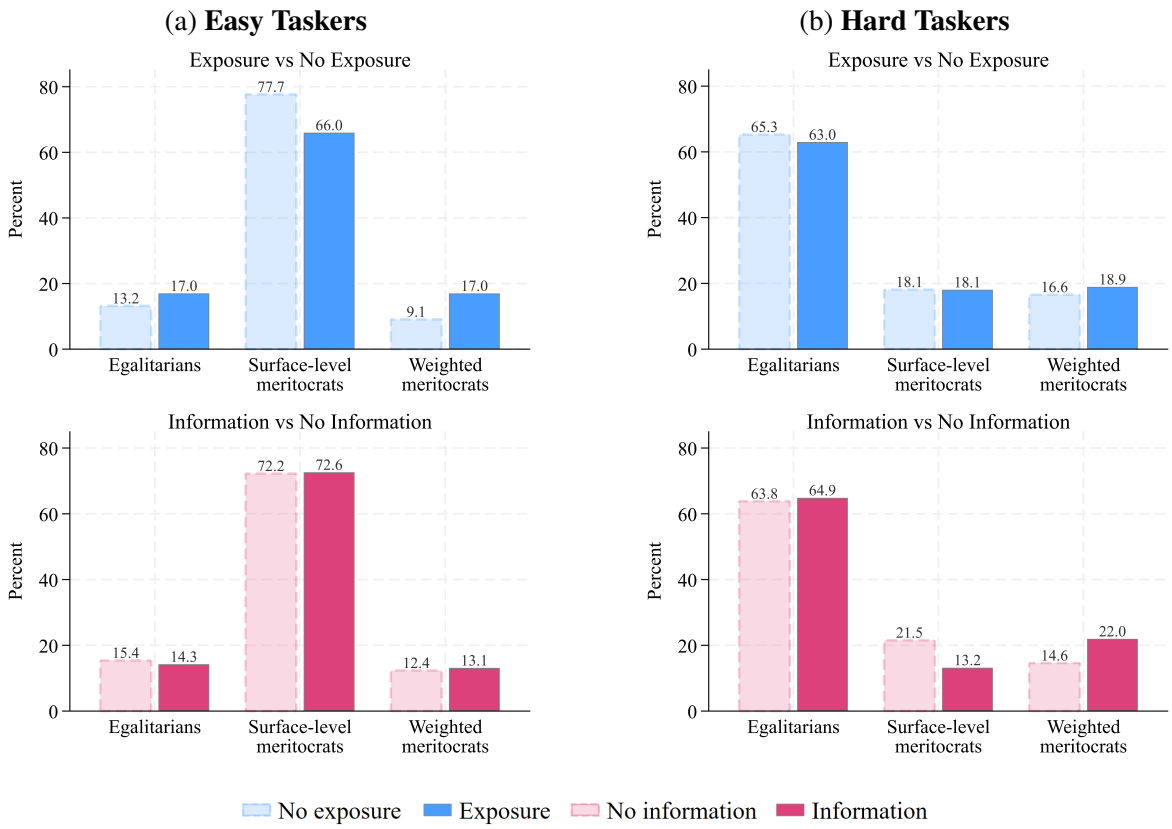
We also estimate the proportion of the three potential fairness types: SE, SM and WM in each of our treatments using an alternative, simpler minimum distance procedure. Specifically, for each individual, we calculate:

$$DEV_i^{SE} = \frac{1}{6}\sum_r \left| \frac{1}{V(\mathbf{q}_r)} \left(y_{ir} - m_i^{SE}(\mathbf{q}_r) \right) \right|$$
$$DEV_i^{SM} = \frac{1}{6}\sum_r \left| \frac{1}{V(\mathbf{q}_r)} \left(y_{ir} - m_i^{SM}(\mathbf{q}_r) \right) \right|$$
$$DEV_i^{WM} = \frac{1}{6}\sum_r \left| \frac{1}{V(\mathbf{q}_r)} \left(y_{ir} - m_i^{WM}(\mathbf{q}_r) \right) \right|$$

which measure, across the six rounds, the average absolute deviation between individual i's initial claim share and the perceived fair share implied by each fairness type. We then classify an individual as the type that gives the lowest average deviation.

Figure D.1 shows the raw proportions of each type, while Table D.1 reports corresponding treatment-effect estimates from random-effects regressions, analogous to those based on the FMM estimates.

Figure D.1: Exposure, Information and estimated types — minimum distance procedure



Notes: Bars report the proportions of participants assigned to the egalitarian, surface-level-meritocratic, and weighted-meritocratic types using the minimum-distance procedure. Exposure comparisons average over Information conditions, while Information comparisons average over Exposure conditions. Table D.1 reports the corresponding regression estimates.

Table D.1: Regression estimates from classification — minimum distance procedure

		Easy Task	
Proportion of:	Egalitarian	Surface-level	Weighted
Exposure	0.042	-0.129*	0.083
	(0.060)	(0.078)	(0.053)
Info	-0.012	0.004	0.008
	(0.057)	(0.069)	(0.043)
Constant	0.135**	0.781***	0.086***
	(0.055)	(0.066)	(0.032)
Observations	221	221	221
		Hard Task	
Proportion of:	Egalitarian	Surface-level	Weighted
Exposure	-0.022	-0.001	0.024
	(0.072)	(0.054)	(0.047)
Info	0.010	-0.083	0.073
	(0.077)	(0.054)	(0.050)
Constant	0.651***	0.216***	0.136***
	(0.061)	(0.037)	(0.037)
Observations	221	221	221

Notes: Session random-effects regressions of individual-level type indicators on Exposure and Information, estimated separately for easy and hard taskers. Each participant is assigned to the fairness type that minimises the average absolute deviation between their six initial claim shares and the perceived fair shares implied by the egalitarian, surface-level-meritocratic, and weighted-meritocratic benchmarks. Session-clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Theory Appendix

E.1 Proofs

Propositions 1 and 2 formalise the directional predictions in the main text, while Proposition 3 motivates the analysis of treatment-effect heterogeneity across relative performance. The propositions are based on comparative statics using the closed-form solution for the proportion claimed by worker i given their preferences:

$$Prop_i^* = \frac{m_i}{V(\mathbf{q})} + \frac{1}{\beta},$$

where

$$m_i = (1-\alpha_i)\Big[\frac{q_i}{q_1+q_2}V(\mathbf{q})\Big] + \alpha_i\Big[\frac{q_i/\bar{q}_i}{q_1/\bar{q}_1+q_2/\bar{q}_2}V(\mathbf{q})\Big].$$

The parameter $\alpha_i \in [0,1]$ captures worker i's degree of cross-role adjustment. To simplify notation, let r denote the observable output of the easy tasker relative to that of the hard tasker, and let $\bar{r}$ denote the corresponding ratio of average performance across the two roles:

$$r := \frac{q_1}{q_2}, \qquad \bar{r} := \frac{\bar{q}_1}{\bar{q}_2}, \qquad r > 0,\ \bar{r} > 1.$$

The proportions claimed by the easy tasker ($i = 1$) and hard tasker ($i = 2$) can then be written as:

$$Prop_1^* = \underbrace{(1-\alpha_1)\frac{r}{r+1} + \alpha_1\frac{r/\bar{r}}{r/\bar{r}+1}}_{\text{Perceived fair share of worker 1}} + \frac{1}{\beta}, \tag{1}$$

$$Prop_2^* = \underbrace{(1-\alpha_2)\frac{1}{r+1} + \alpha_2\frac{1}{r/\bar{r}+1}}_{\text{Perceived fair share of worker 2}} + \frac{1}{\beta}. \tag{2}$$

Under weighted meritocracy ($\alpha_i = 1$), average relative performance $r = \bar{r}$ implies a perceived fair share of one half for each worker. The self-interest markup $1/\beta$ is constant in r and α_i and therefore does not affect the comparative statics below.

Proposition 1 (**Effect of relative performance**). *A rise in r increases (decreases) the proportion claimed by the easy (hard) tasker.*

Proof. Noting that $\alpha_1, \alpha_2 \in [0, 1]$ and $r, \bar{r} > 0$,

For the easy tasker,

$$\frac{\partial Prop_1^*}{\partial r} = (1 - \alpha_1)\frac{1}{(r+1)^2} + \alpha_1 \frac{\bar{r}}{(r+\bar{r})^2} > 0,$$

Hence, the proportion demanded by the easy tasker increases with relative performance.

For the hard tasker,

$$\frac{\partial Prop_2^*}{\partial r} = -(1 - \alpha_2)\frac{1}{(r+1)^2} - \alpha_2 \frac{\bar{r}}{(r+\bar{r})^2} < 0.$$

Hence, the proportion demanded by the hard tasker decreases with relative performance.

□

Proposition 2 (**Effect of cross-role adjustment**). *A rise in α_i decreases (increases) the proportion demanded by the easy (hard) tasker.*

Proof. Noting that $r > 0$ and $\bar{r} > 1$,

For the easy tasker,

$$\frac{\partial Prop_1^*}{\partial \alpha_1} = \frac{r(1 - \bar{r})}{(r+1)(r+\bar{r})} < 0,$$

Hence, greater cross-role adjustment decreases the proportion demanded by the easy tasker.

For the hard tasker,

$$\frac{\partial Prop_2^*}{\partial \alpha_2} = \frac{r(\bar{r} - 1)}{(r+1)(r+\bar{r})} > 0.$$

Hence, greater cross-role adjustment increases the proportion demanded by the hard tasker.

□

Proposition 3 (Interaction between cross-role adjustment and relative performance). *Suppose $\bar{r} > 1$. The magnitude of the change in the proportion demanded induced by an increase in cross-role adjustment increases with r when $r < \sqrt{\bar{r}}$ and decreases with r when $r > \sqrt{\bar{r}}$. It is greatest at $r = \sqrt{\bar{r}}$.*[2]

Proof. Noting that $\bar{r} > 1$ and $r > 0$,

For the easy tasker,

$$\frac{\partial^2 Prop_1^*}{\partial \alpha_1 \, \partial r} = \frac{(1-\bar{r})(\bar{r} - r^2)}{(r+\bar{r})^2 (r+1)^2}.$$

The denominator is always positive, while the numerator is positive if and only if $r > \sqrt{\bar{r}}$.

Because $\partial Prop_1^*/\partial \alpha_1 < 0$, the magnitude of the effect becomes larger as r increases when $r < \sqrt{\bar{r}}$ and smaller when $r > \sqrt{\bar{r}}$. Since the cross-partial changes from negative to positive at $r = \sqrt{\bar{r}}$, the magnitude of the effect is greatest at this point.

For the hard tasker,

$$\frac{\partial^2 Prop_2^*}{\partial \alpha_2 \, \partial r} = \frac{(\bar{r}-1)(\bar{r} - r^2)}{(r+\bar{r})^2 (r+1)^2}$$

The denominator is always positive, while the numerator is positive if and only if $r < \sqrt{\bar{r}}$.

Since $\partial Prop_2^*/\partial \alpha_2 > 0$, the magnitude of the effect likewise becomes larger as r increases when $r < \sqrt{\bar{r}}$ and smaller when $r > \sqrt{\bar{r}}$. Since the cross-partial changes from positive to negative at $r = \sqrt{\bar{r}}$, the magnitude of the effect is again greatest at this point.

□

E.2 Egalitarian individuals

The benchmark framework focuses on meritocratic fairness ideals, with α_i capturing the degree of cross-role adjustment between surface-level and weighted meritocracy. Workers may, however, also place weight on egalitarian considerations. To allow for this, let $\lambda_i \in [0, 1]$ denote the weight worker i places on an equal split. Perceived fair allocations then take the form:

$$m_{i,E} = \lambda_i \frac{V(\mathbf{q})}{2} + (1-\lambda_i) \left\{ (1-\alpha_i) \left[\frac{q_i}{q_1+q_2} V(\mathbf{q}) \right] + \alpha_i \left[\frac{q_i/\bar{q}_i}{q_1/\bar{q}_1 + q_2/\bar{q}_2} V(\mathbf{q}) \right] \right\}.$$

[2] Because $\bar{r} > 1$, the threshold $\sqrt{\bar{r}}$ lies below average relative performance, $\bar{r}$. In our experiment, approximately 84.6% of pairs have a relative performance above $\sqrt{\bar{r}}$, so the declining portion of the comparative static applies to most of the observed data.

When $\lambda_i = 0$, this reduces to the benchmark meritocratic framework. When $\lambda_i = 1$, worker i is a strict egalitarian and perceives an equal split as fair regardless of relative performance. Intermediate values place positive weight on both egalitarian and meritocratic considerations. Importantly, α_i retains its interpretation as the degree of cross-role adjustment within the meritocratic component.

This extension is particularly relevant for hard taskers, whose observable performance is lower than that of easy taskers in approximately 98% of rounds. Hard taskers may therefore place greater weight on egalitarian allocations, whether because of underlying fairness preferences or self-serving interpretations of fairness. Such preferences would make their perceived fair allocations closer to an equal split and their claims less responsive to relative performance.

For the hard tasker, the proportion demanded is

$$Prop^*_{2,E} = \frac{\lambda_2}{2} + (1-\lambda_2)\left[(1-\alpha_2)\frac{1}{r+1} + \alpha_2\frac{\bar{r}}{r+\bar{r}}\right] + \frac{1}{\beta}.$$

The effect of cross-role adjustment is

$$\frac{\partial Prop^*_{2,E}}{\partial \alpha_2} = (1-\lambda_2)\frac{r(\bar{r}-1)}{(r+1)(r+\bar{r})} > 0.$$

Compared with the benchmark meritocratic case, the effect is therefore scaled by $1-\lambda_2$. Greater weight on egalitarianism reduces the extent to which an increase in cross-role adjustment raises the hard tasker's demand, and the effect disappears entirely for a strict egalitarian.

Egalitarianism also weakens the relationship between demands and relative performance:

$$\frac{\partial Prop^*_{2,E}}{\partial r} = (1-\lambda_2)\left[-(1-\alpha_2)\frac{1}{(r+1)^2} - \alpha_2\frac{\bar{r}}{(r+\bar{r})^2}\right] < 0.$$

Thus, greater weight on egalitarianism both moves perceived fair allocations towards an equal split and makes demands less sensitive to relative performance. This provides one possible explanation for why hard taskers' claims are closer to 50–50 and less responsive to relative performance, while Exposure and Information generate weaker changes in their claims.

F Experiment Materials

F.1 Instructions

No Information treatment (Easy Grid/ Hard Slider)

Ground Rules

Welcome to the study, please read the information below carefully. If you have questions at any point, please raise your hand and an experimenter will come over to attend to you.

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All earnings will be denominated in Experimental Currency Units (ECUs). The conversion rate is 140 ECUs = 1 SGD**.** In addition, you will also receive a completion fee of 4 SGD. This money will be paid to you privately at the end of the study.

Introduction

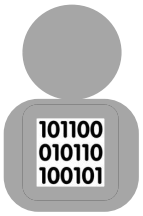
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Each of you will perform a set of tasks which will generate a pool of ECUs. Subsequently, you will have to decide how to split this pool of ECUs with your counterpart.

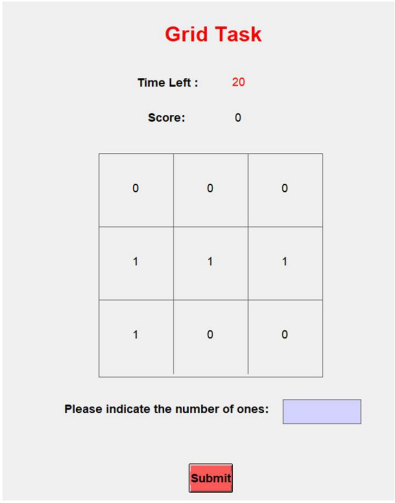
Professions

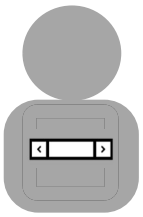
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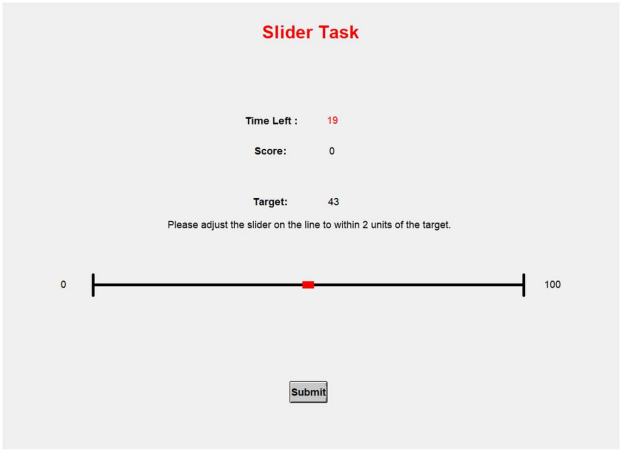


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Slider Profession: In the slider profession, you will see a line on the screen representing values from 0 to 100 and be given a number. Your task is to use your mouse to adjust the red slider on the line (drag/click) within 2 units of the stated target. You can readjust your answer an unlimited number of times. Once you are done, click "Submit". If the red slider is within the range, a new target will appear. If not, you will be informed if your answer is too high or too low and have to resubmit an answer.



Your performance or score for each task will be equal to the number of correctly submitted answers.

Training Stage

Before you begin production, you will have a warm-up and spend some time on training in your profession. The exact details will be provided before the training begins.

Since your future performance in your profession's task will affect your payoffs, you should try your best in the training to get as used to the task as possible.

Production Stage

After training, you will begin production. There will be several rounds of production.

In each round of production, you will be randomly paired up with a new participant *belonging to a different profession from you*.

Each round of production consists of 2 stages:

1. Working phase – in which your pair works to generate a pool of ECUs.
2. Allocation phase – in which your pair decides how to split the ECUs earned.

Working Phase

In this phase, you and your counterpart will be given 2 minutes to complete the task associated with your profession. At the end of the working phase, both of you will receive a score based on the number of correct answers submitted.

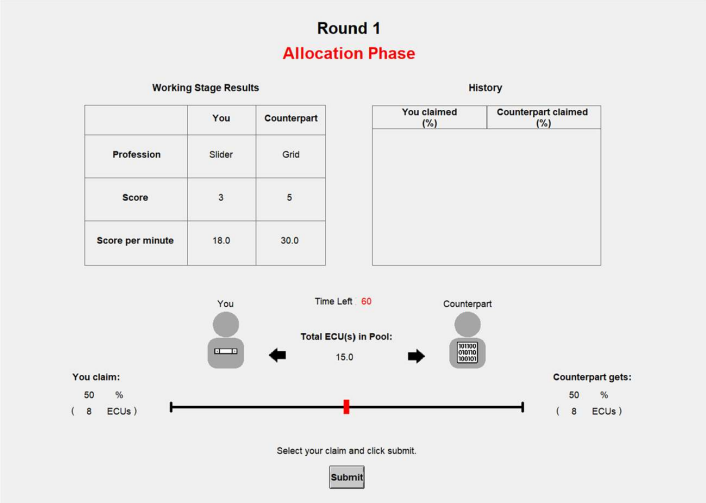
The pool of ECUs generated will depend on both your scores in your individual tasks. Specifically, the pool of ECUs generated will be equal to $A \times B$, whereby A is your score, while B is your counterpart's score.

For example, suppose you are assigned a "grid" profession and your counterpart is assigned a "slider" profession. If your score in the grid task is 16 and your counterpart's score in the slider task is 21, then the pool of ECUs generated will be $\mathbf{16 \times 21 = 336.}$

Allocation Phase

In this phase, your pair will have **5 minutes** to reach an agreement on how to split the pool of ECUs generated in the Working Phase. You do not have to use up all the time, but must not exceed it.

On the screen, you will be shown the pool of ECUs, as well as your score and your counterpart's score. Both of you will then get to simultaneously claim a percentage of the pool (in steps of 5%) using a slider as shown below.



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<u>Post Round</u>

After each round of production, you will be asked several questions. You will then move on to the next round, with a new counterpart. There will be 6 production rounds in total.

Post-Experiment

<u>Total Earnings</u>

Your total earnings for the experiment will be the sum of the ECUs earned in **two randomly selected production rounds.** This will be converted to SGD and added to your completion fee.

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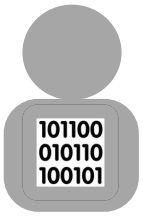
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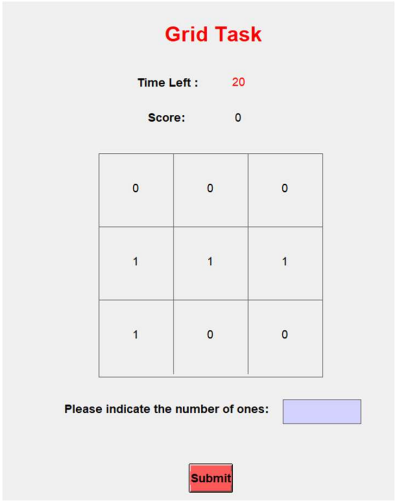
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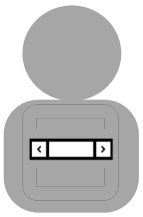
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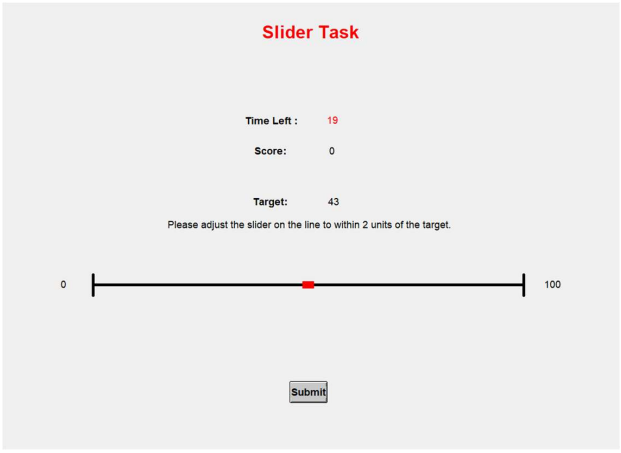


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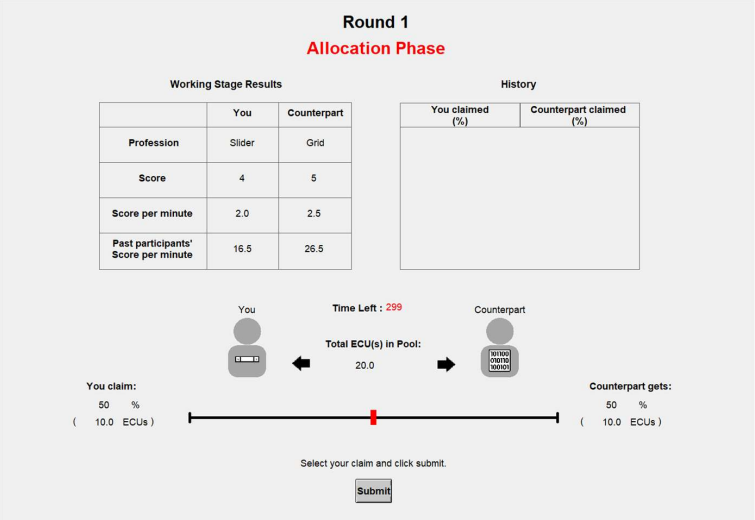
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Post-Experiment

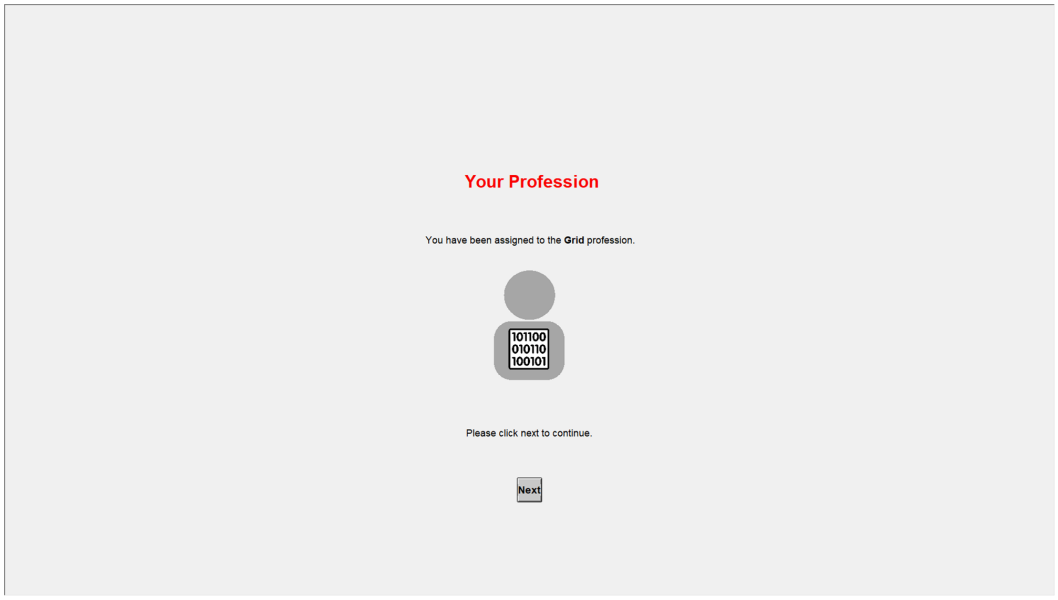
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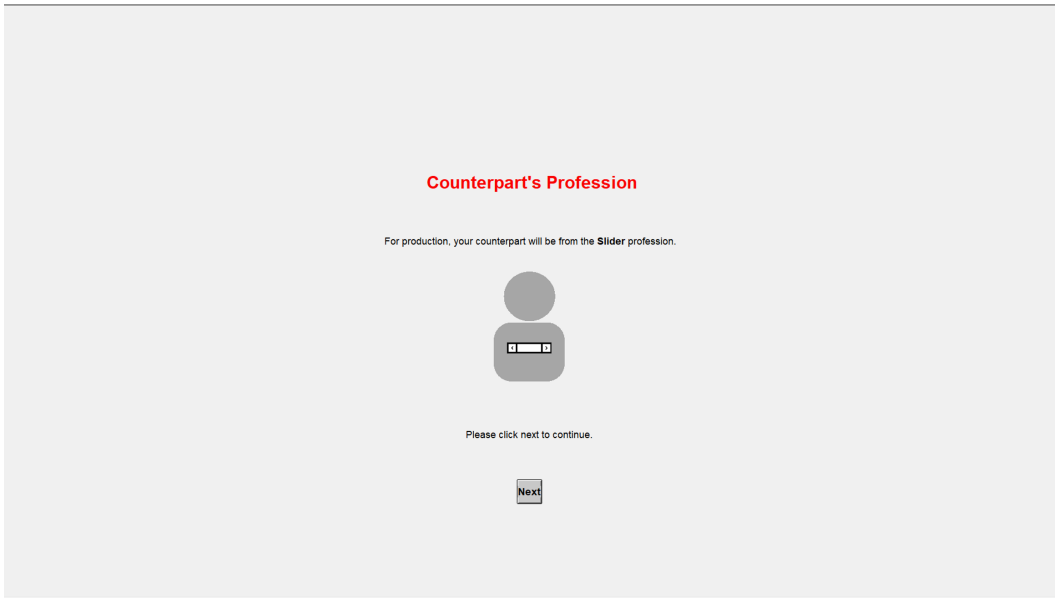
<u>Questionnaire</u>

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F.2 Experiment Screenshots

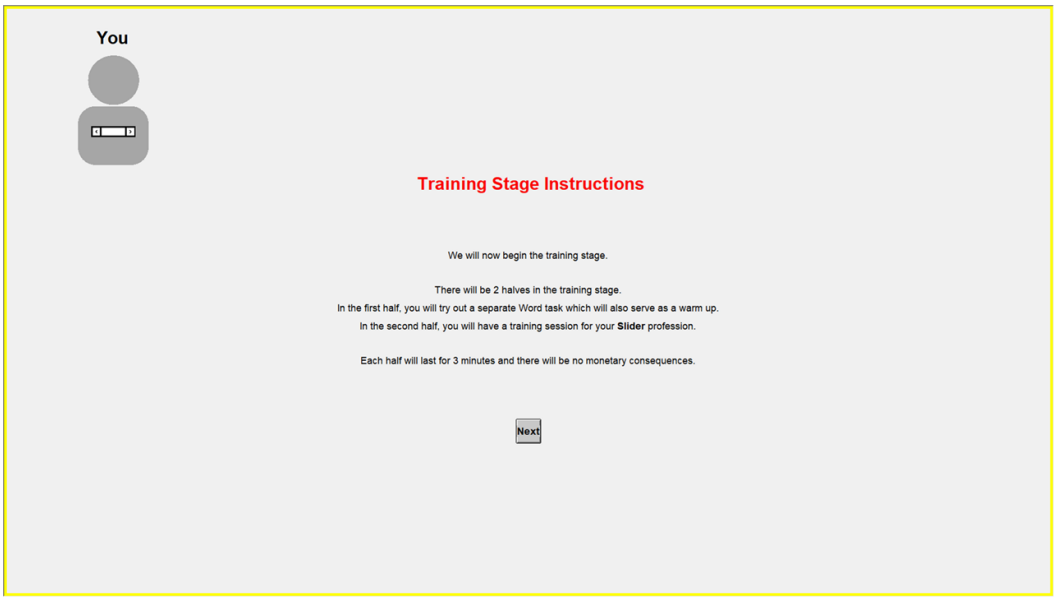


(a) Own Profession

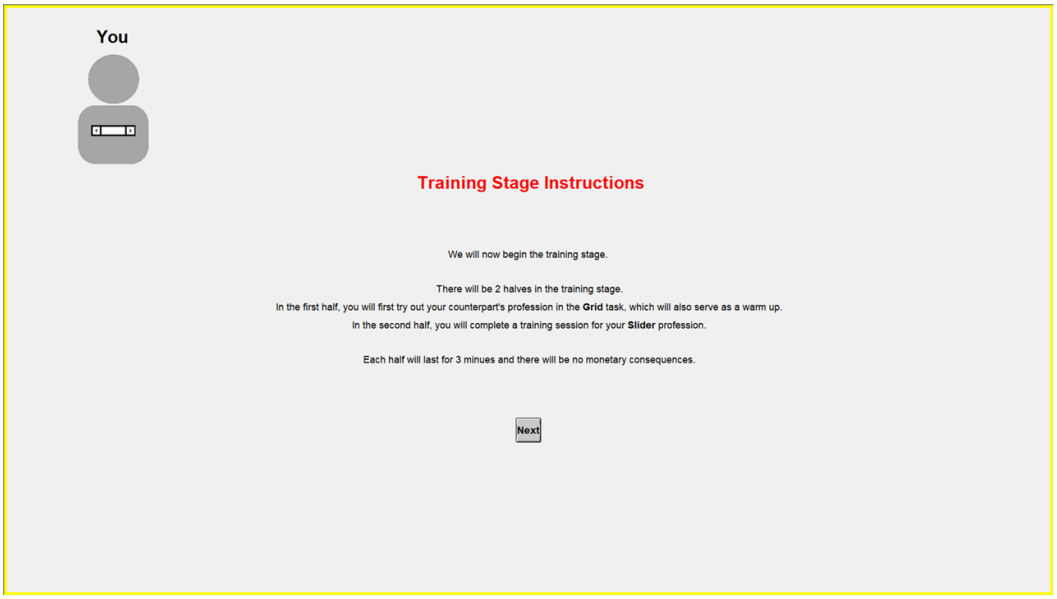


(b) Counterpart's Profession

Assignment of Professions

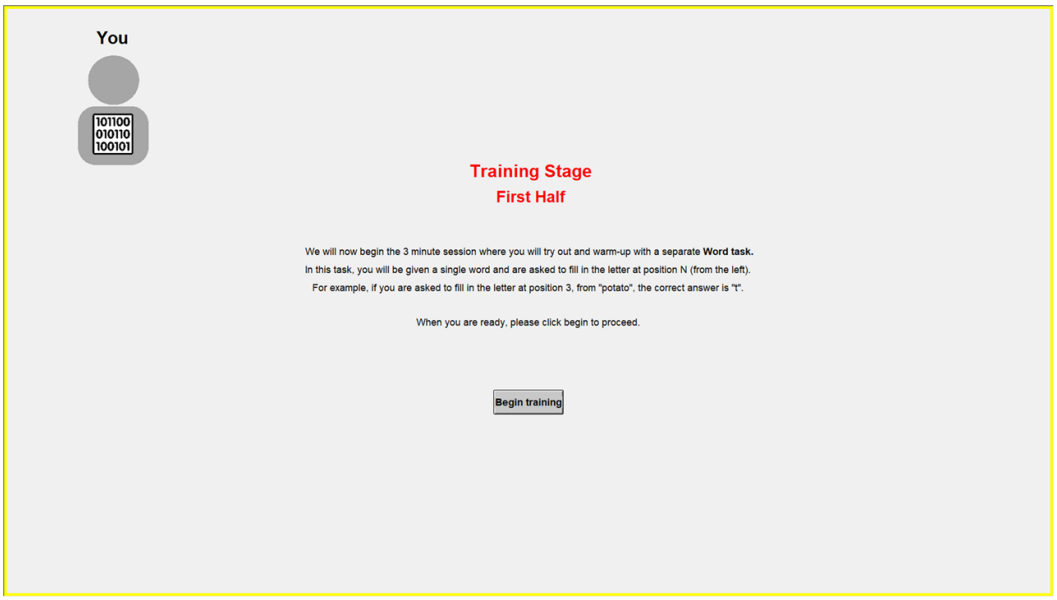


(a) No Exposure Treatment

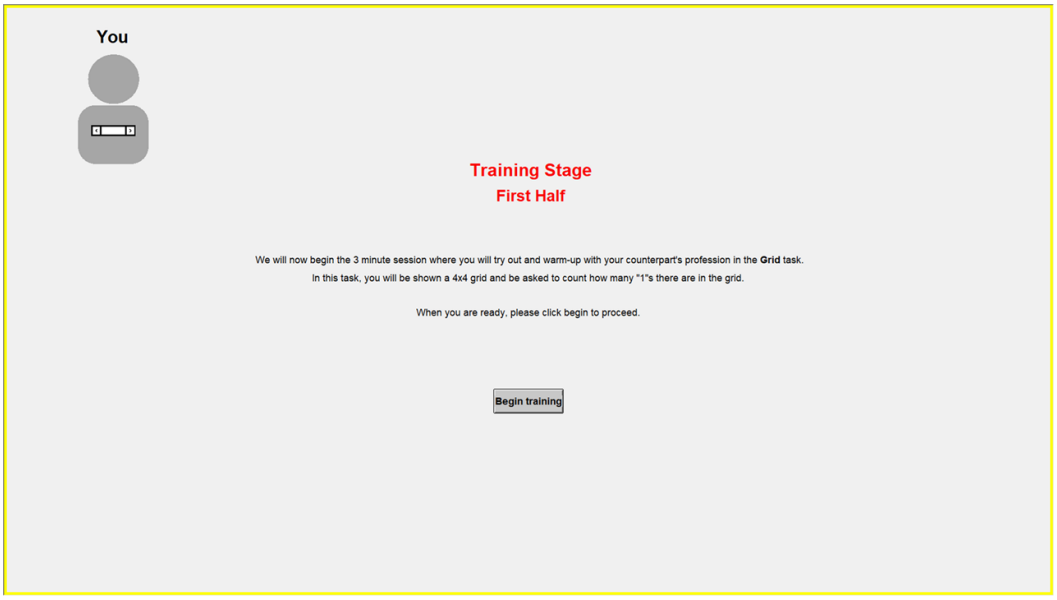


(b) Exposure Treatment

Training Stage Instructions

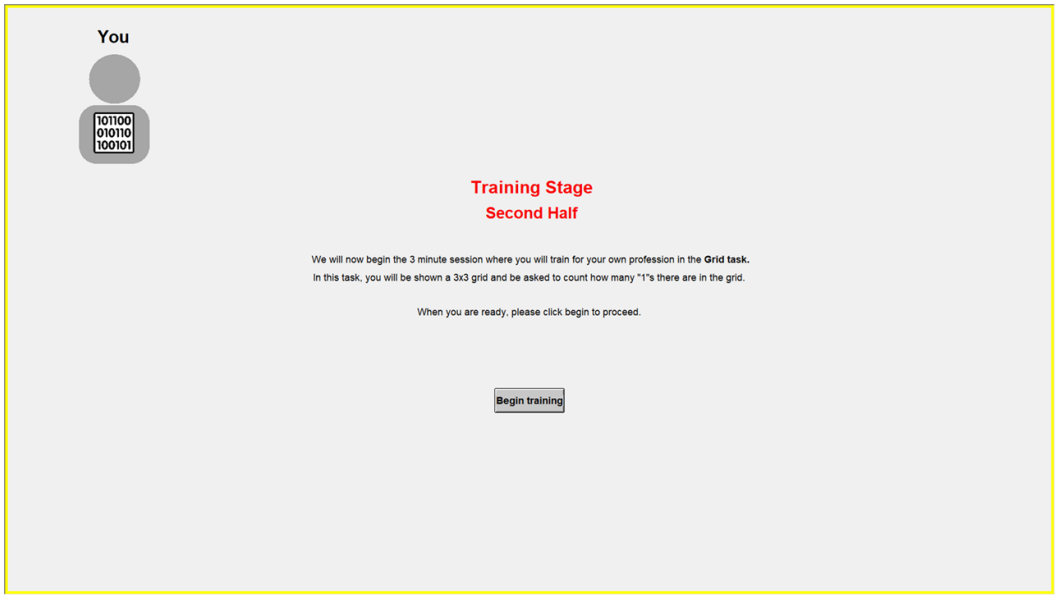


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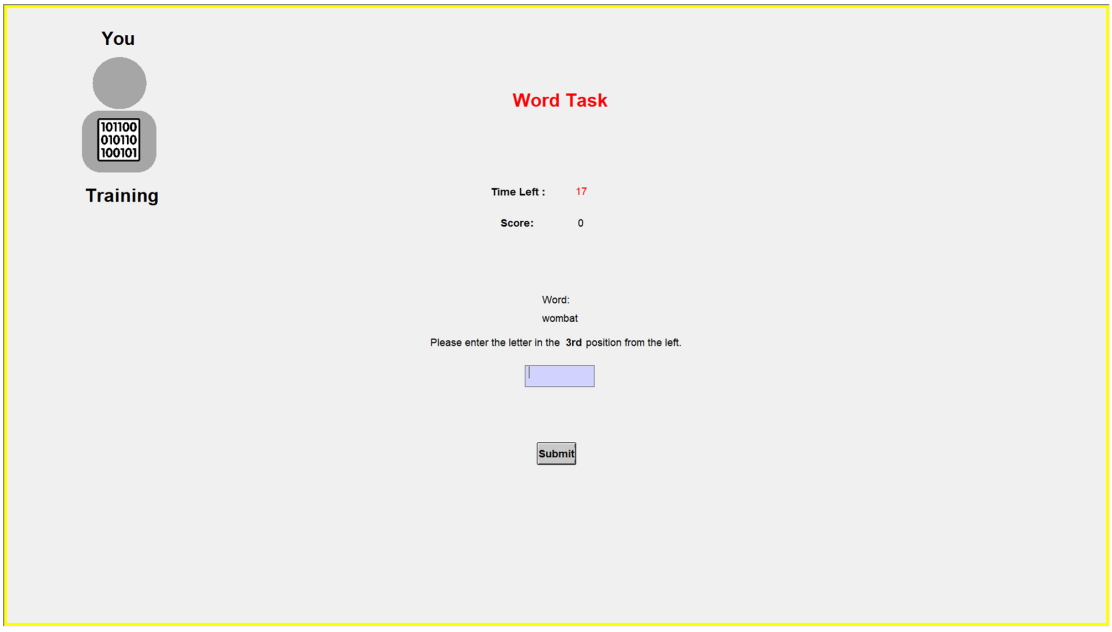


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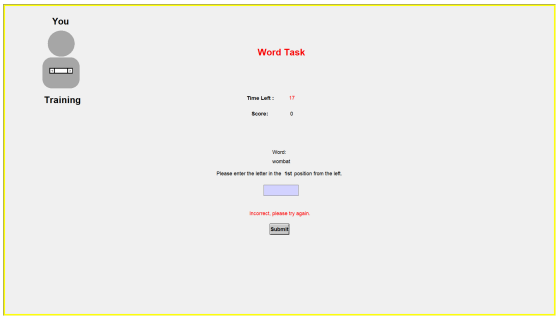
Training Stage 1



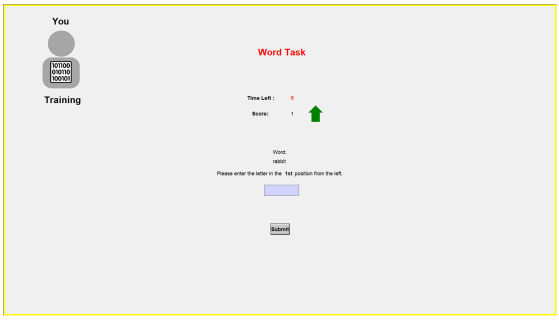
Training Stage 2



(a) Default

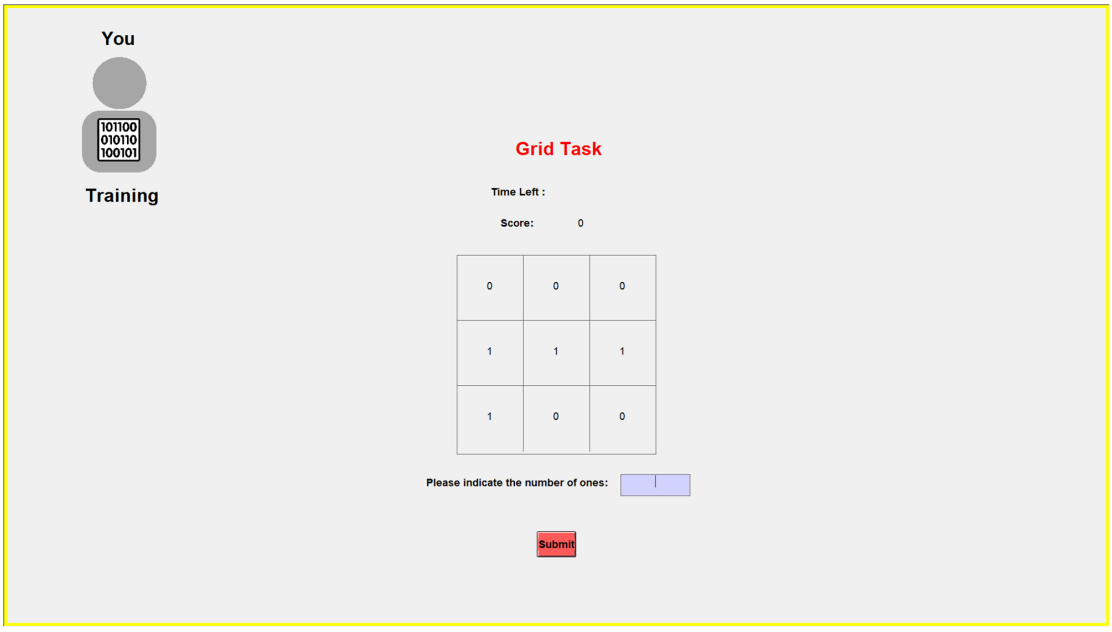


(b) Incorrect answer

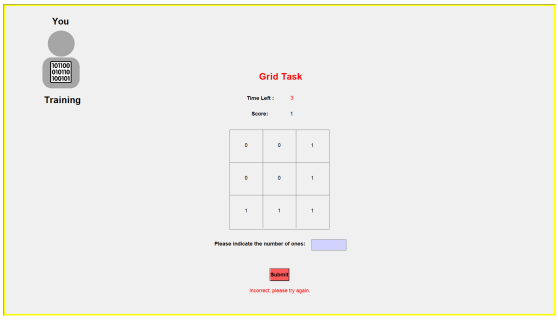


(c) Correct answer

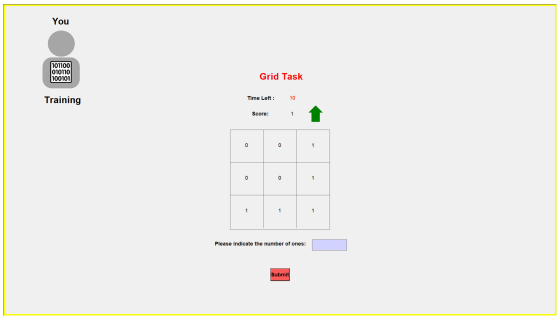
Warm-up task (Word)



(a) Default

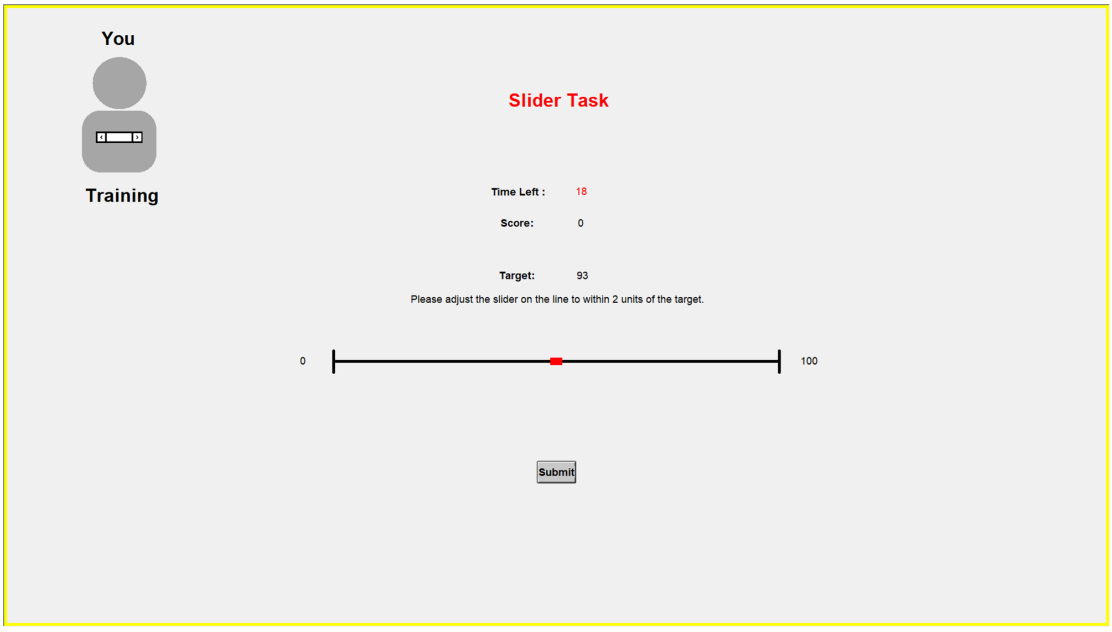


(b) Incorrect answer

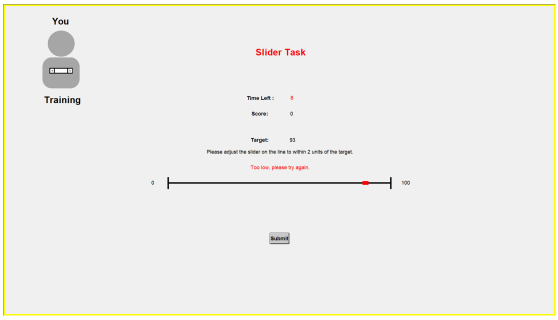


(c) Correct answer

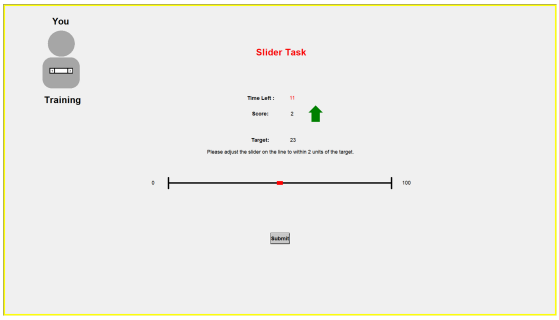
Practice/Warm-up task (Grid)



(a) Default

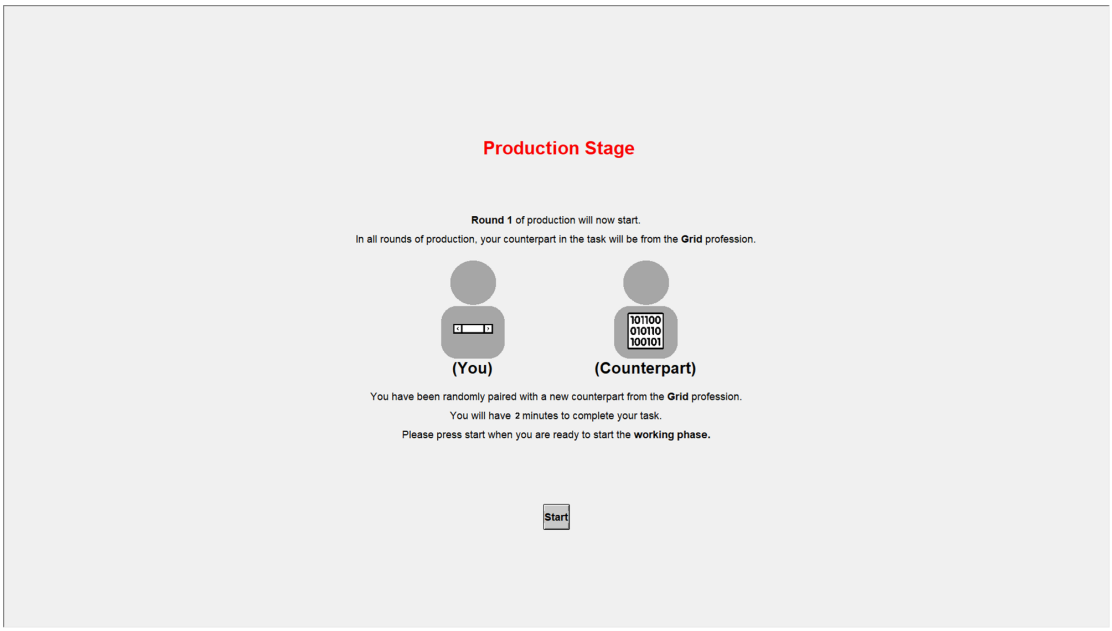


(b) Incorrect answer

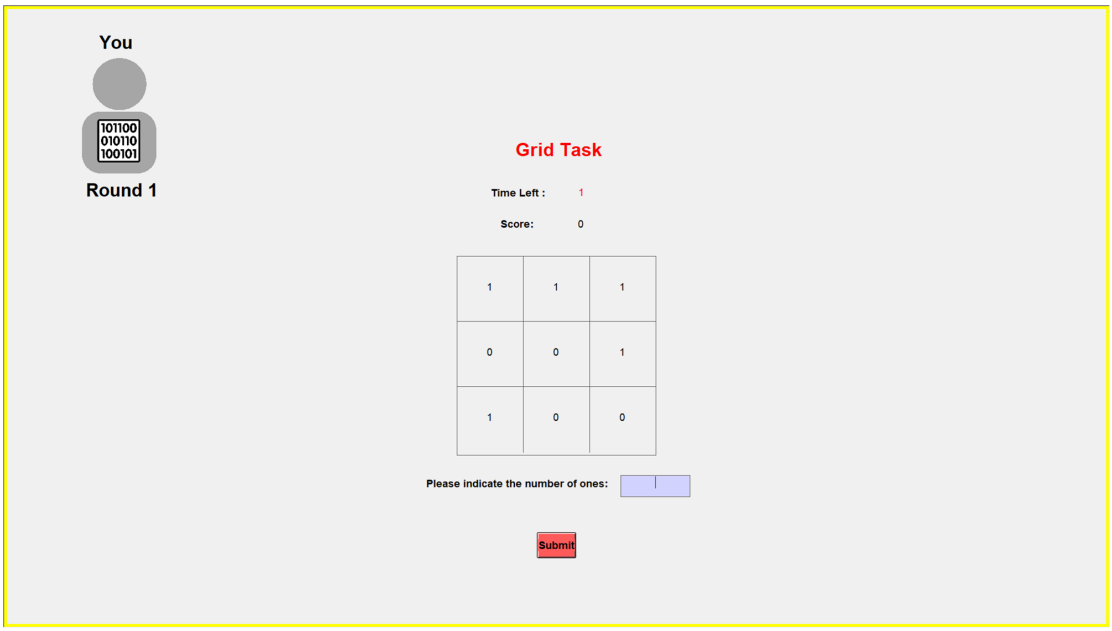


(c) Correct answer

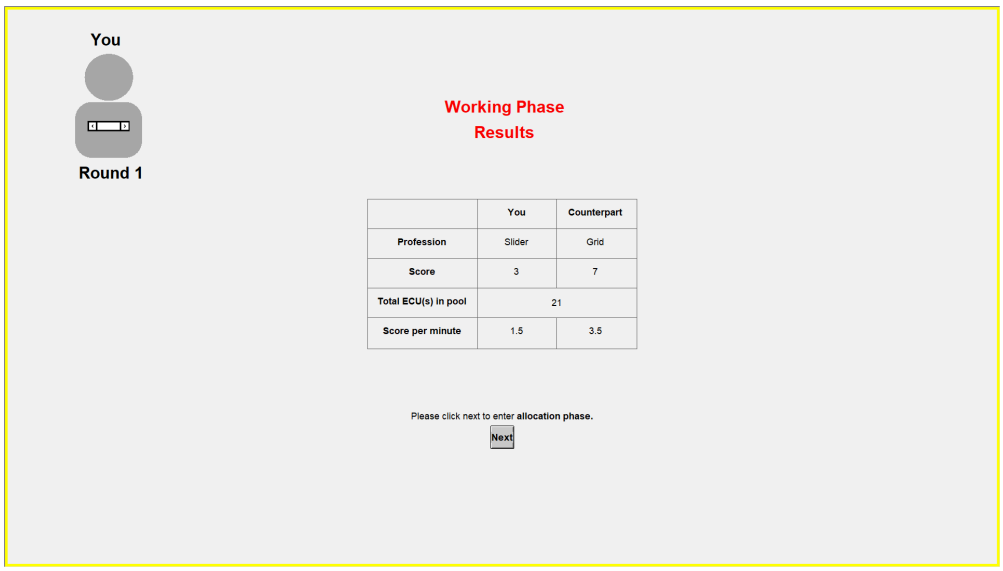
Practice/Warm-up task (Slider)



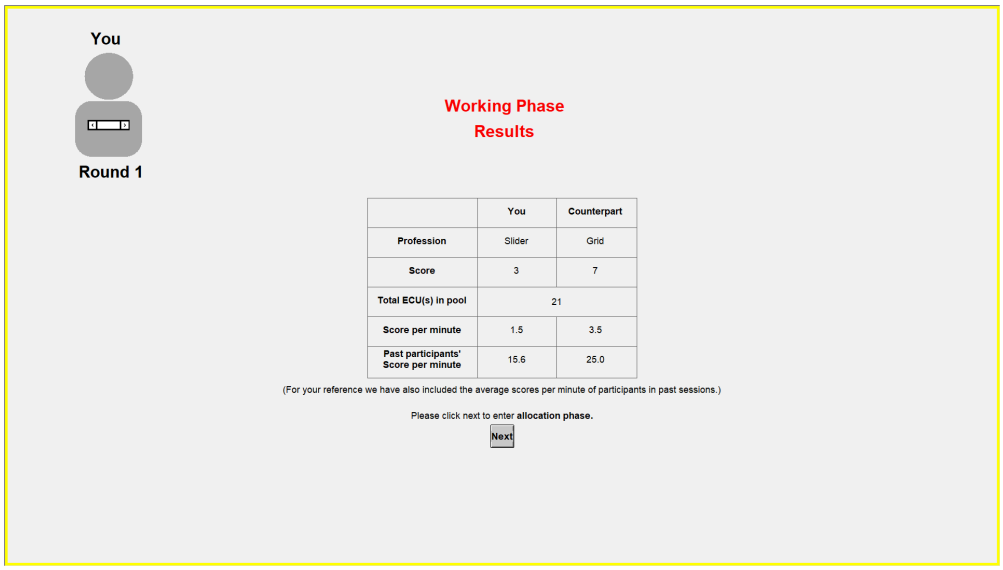
Round Instructions



Production Task

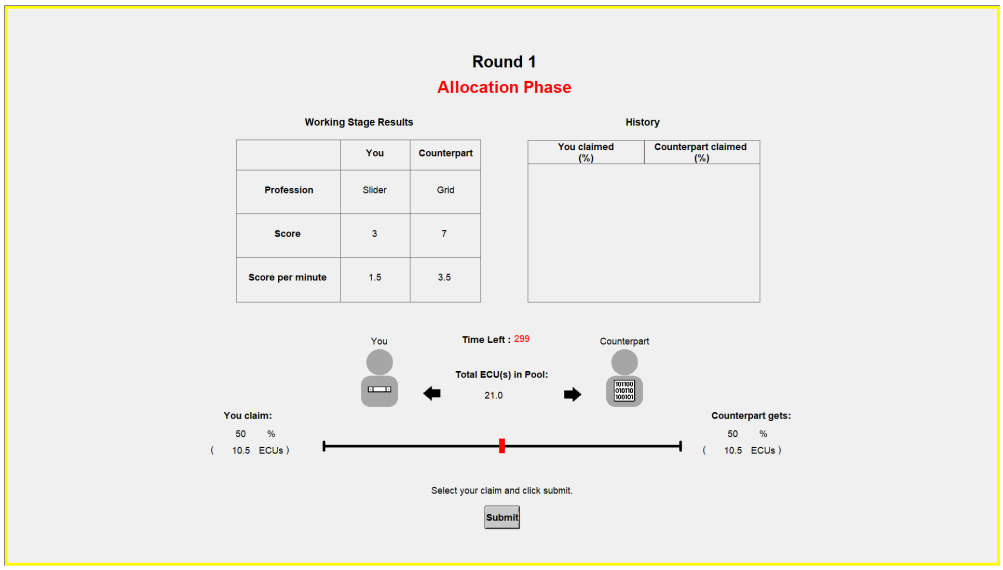


(a) No Information

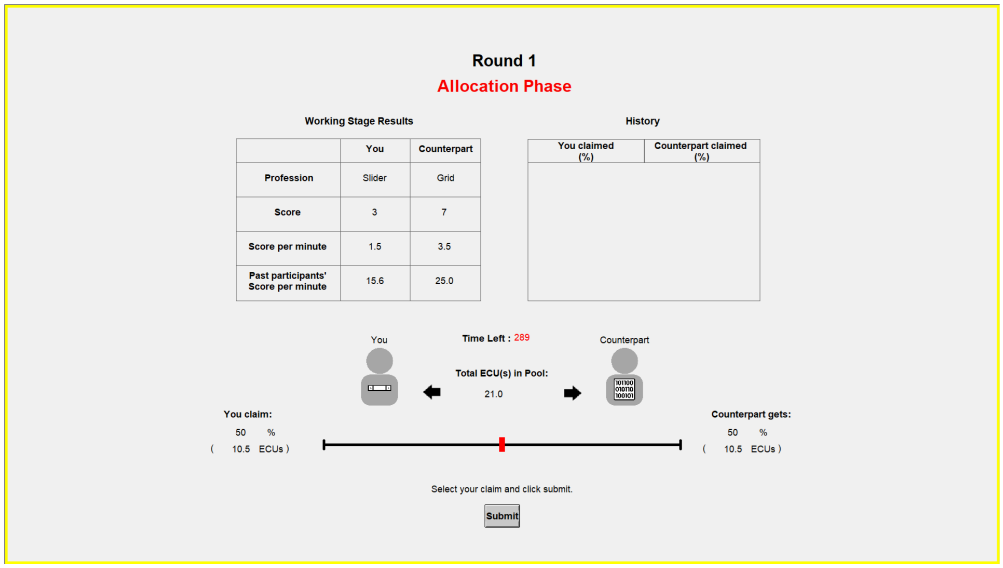


(b) Information

Production Results

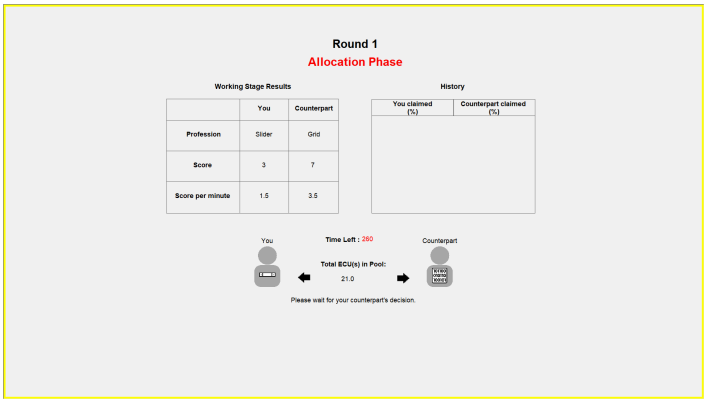


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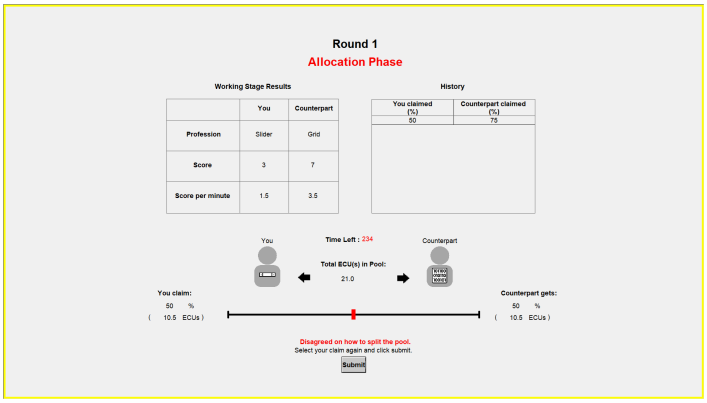


(b) Information

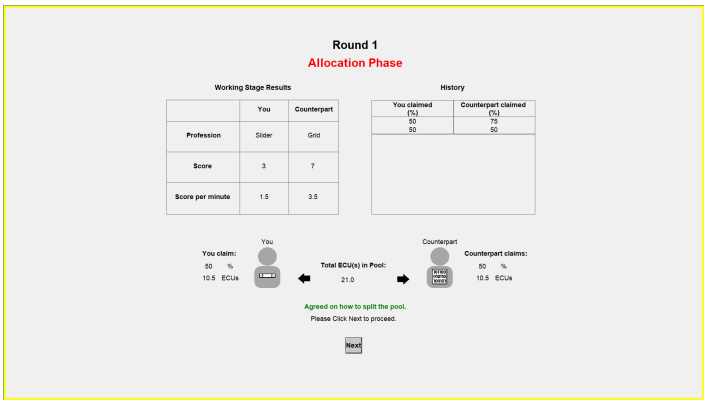
Bargaining Phase



(a) Waiting



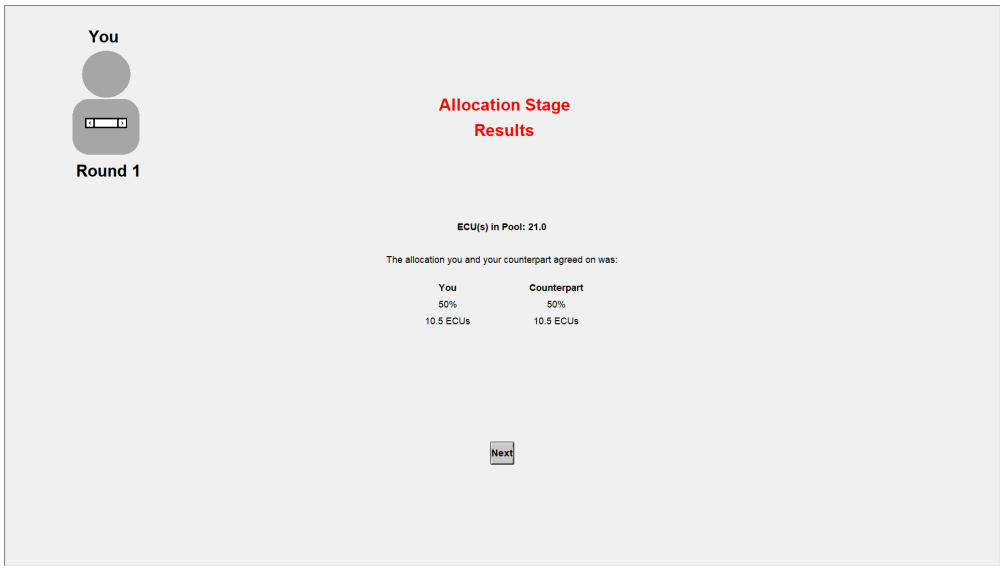
(b) Disagreement



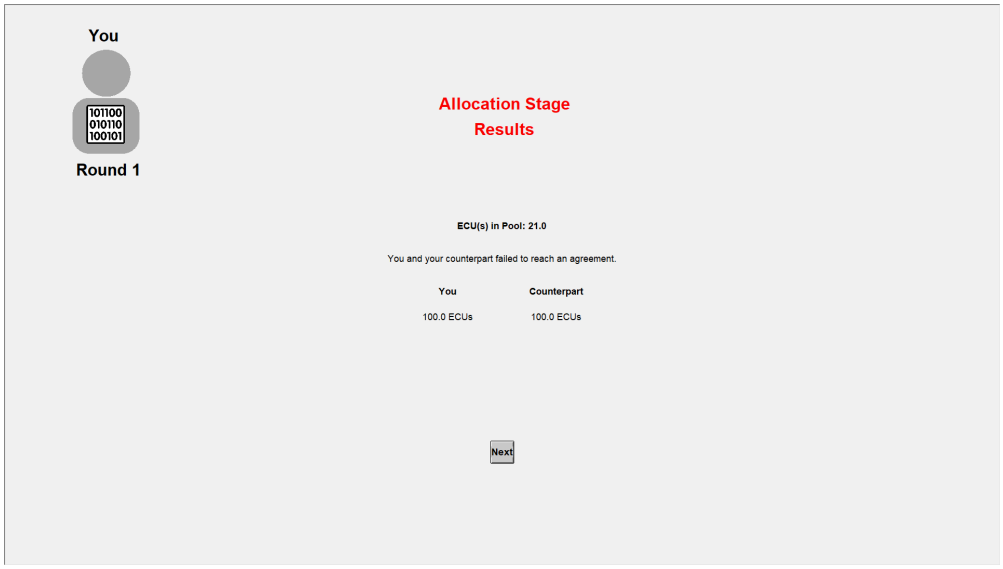
(c) Agreement

Bargaining Phase (Feedback)

(Only shows examples for No Information treatment. For Information treatment differences, see previous page.)

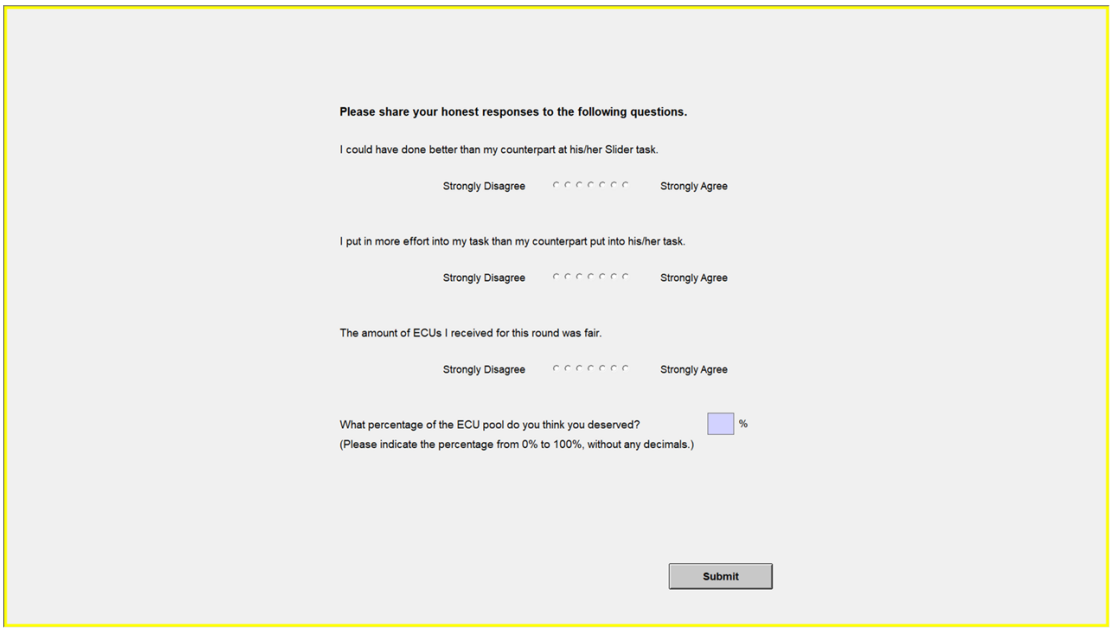


(a) Agreement

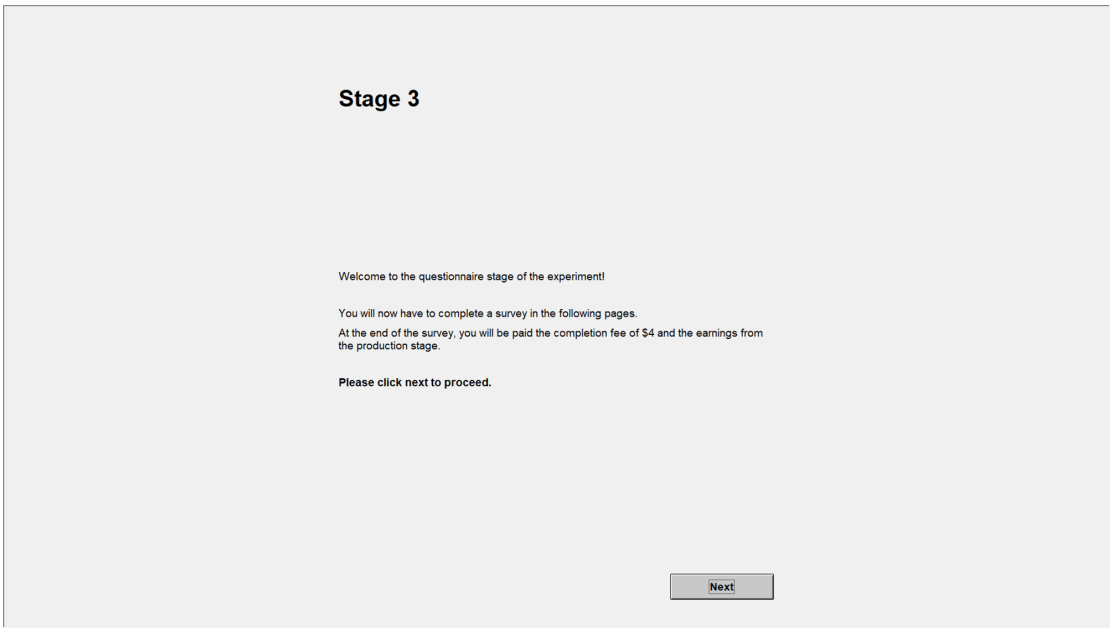


(b) Disagreement

Bargaining Results



Post-Round Survey



Post-Experiment survey Instructions

F.3 Post-Experiment Survey

Open ended questions

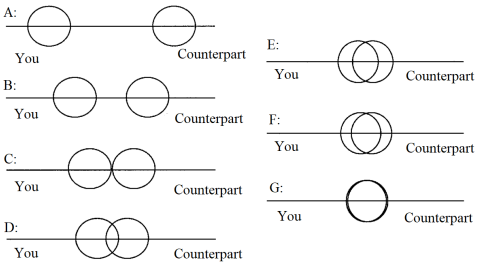
Please share your honest responses to the following questions.

Was there anything unclear about the instructions? If so, please state so. [*Open-ended*]

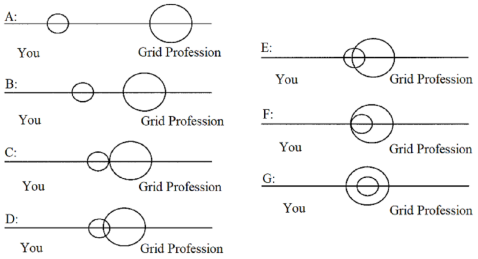
When deciding on the percentage of the pool to demand, what were the factors most important to you? [*Open-ended*]

Feelings of Closeness

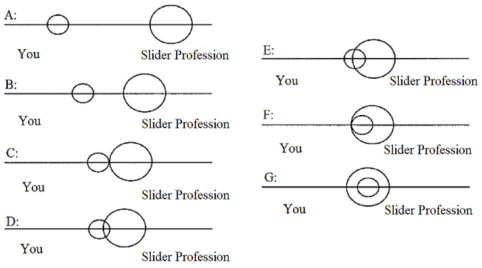
Please select the picture that best describes on average, your feelings of closeness towards your counterpart in production.



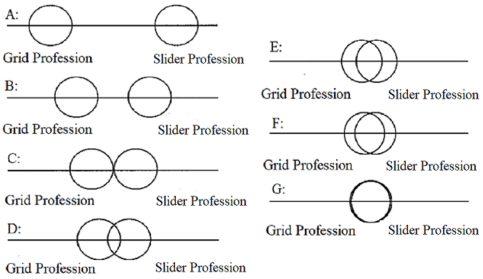
Please select the picture that best describes on average, your feelings of closeness towards the group of participants belonging to the Grid profession.



Please select the picture that best describes on average, your feelings of closeness towards the group of participants belonging to the Slider profession.



Please select the picture that best describes on average, your feelings of closeness of the two groups of participants belonging to the Grid and Slider profession.



Questions about joint production task

Please share your honest responses to the following questions.

Overall, how satisfied are you with your outcomes in production?
[*1: Not at all - 7: Completely*]

In production, to what extent did you feel that cooperation was needed between you and your counterpart to maximise your earnings?
[*1: Not at all - 7: Completely*]

When working on your profession's task, on average, how much effort did you feel you were putting into it? (Please indicate the percentage from 0% to 100%, where 100% is your maximum effort.)

My task in the Grid (Slider) profession is harder than my Counterpart's task in the Slider (Grid) profession.
[*1: Strongly Disagree - 7: Strongly Agree*]

I did not understand what my counterpart's task is about.
[*1: Strongly Disagree - 7: Strongly Agree*]

People in my Grid (Slider) profession should earn more than people in the Slider (Grid) profession.
[*1: Strongly Disagree - 7: Strongly Agree*]

I was satisfied with my allocation of earnings in production.
[*1: Strongly Disagree - 7: Strongly Agree*]

When working on my profession's task, I was affected by what happened in past allocations.
[*1: Strongly Disagree - 7: Strongly Agree*]

I found it hard to come to an agreement on the allocation of earnings with my counterparts in production.
[*1: Strongly Disagree - 7: Strongly Agree*]

In future, if I am working in a firm that requires two or more different jobs, I would want to try out my colleagues' jobs.
[*1: Strongly Disagree - 7: Strongly Agree*]

I prefer to work with someone who knows what my work is about.
[*1: Strongly Disagree - 7: Strongly Agree*]

Suppose you could have a third party decide on the allocation of the pool of ECUs, would you want him to be in the Grid profession, Slider profession, or have experience in both professions?
[*Grid, Slider, Both*]

Demographic questions

Gender [*Female, Male, I would prefer not to say*]

Course of study [*Open-ended*]

Year of study [*Year 1, Year 2, Year 3, Year 4, Year 5, Postgraduate, Not Applicable*]

Nationality [*Open-ended*]

Ethnicity [*Open-ended*]