CSEF
Centre for Studies in Economics and Finance

WORKING PAPER NO. 681

Gender-science Implicit Association and Employment Decisions

Francesca Gioia and Giovanni Immordino

September 2023

University of Naples Federico II
University of Salerno
Bocconi University, Milan

CSEF - Centre for Studies in Economics and Finance
DEPARTMENT OF ECONOMICS AND STATISTICS – UNIVERSITY OF NAPLES FEDERICO II
80126 NAPLES - ITALY
Tel. and fax +39 081 675372 – e-mail: csef@unina.it
ISSN: 2240-9696

CSEF
Centre for Studies in Economics and Finance

WORKING PAPER NO. 681

Gender-science Implicit Association and Employment Decisions

Francesca Gioia[*] and Giovanni Immordino[†]

Abstract
In this paper, we document that implicit associations, measured by the gender-science implicit association test, explain employment decisions, both in terms of access to the labour market and in terms of career advancement. In both cases, when choosing between a female and a male worker with the same ex-ante ability, the higher the male-science implicit association of the employer, the higher her/his likelihood of hiring/promoting a male intentionally and the lower her/his likelihood of leaving the decision to chance. Increasing the incentives to employers does not vary the effect of implicit gender-science association which is also not heterogeneous by gender, age or income earned.

JEL Classification: J16, J24

Keywords: Gender, Labor discrimination, Implicit Association.

---

[*] Università degli Studi di Milano. E-mail: francesca.gioia@unimi.it *(Corresponding author)*

[†] Università di Napoli Federico II and CSEF. E-mail: giovanni.immordino@unina.it

1. Introduction

A recent literature has investigated the factors contributing to discrimination against women in the workplace. Despite this large and growing literature, important open questions about gender discrimination remain. Specifically, it is difficult to understand what factors contribute to discriminatory behavior and, more importantly, what specific policy interventions could best redress gender inequality.

The previous two questions are clearly related. Indeed, if discrimination is rooted in preferences (Becker, 1957) — so called taste-based discrimination — the bias is conscious and possible remedies are limited by the difficulty of fixing tastes. Conversely, discrimination could be, mainly or exclusively, statistical, that is based on beliefs about average gender differences in abilities or skills. In this case, both correct belief-based statistical discrimination (Arrow, 2015; Phelps, 1972) and incorrect belief-based statistical discrimination (Bordalo et al., 2016) can be classified, differently from taste-based discrimination, as unconscious bias.[1]

In this paper, we gauge unconscious gender stereotypes — measured by the gender-science implicit association test — and we appraise their relevance as a driver of discrimination specific to gender and robust to two variations in the decision environment: different size of the incentives and different employment decisions (hiring *vs* career advancement).

In a carefully designed experiment Coffman et al. (2021) shows that, on average, employers prefer to hire male over female workers for male-typed tasks, even when the two workers are otherwise identical. Using a control condition, the authors also show that this discrimination is not specific to gender since employers are less willing to hire a worker from a group that performs worse on average, even when this group is defined by non-stereotypical characteristics. Coffman et al. (2021) concludes that the key driver of discrimination against women, in their setting, is belief-based. Thus, unconscious bias may play a role. Our experiment closely follows Coffman et al. (2021) to study the role that unconscious gender stereotypes play on such a belief-based discrimination. Our hypothesis is that subjects with a stronger implicit sex-science stereotype, such that males are seen as more capable in these fields, are more likely to discriminate against

---

[1] On this see the comprehensive survey by Della Giusta and Bosworth (2020), which illustrates the psychology of bias and stereotyping, clearly describes how these insights have been incorporated into theoretical and empirical research in economics, and presents the literature on remedies to contrast bias.

female workers.

Nonetheless, even though these gender stereotypes may operate on an unconscious level, they can potentially be overridden by other motivations. To begin with, when employers face greater monetary incentives to hire more productive workers, the allure of increased potential earnings might lead to more thoughtful decision-making, thereby mitigating the influence of unconscious bias. To explore this possibility, we examine whether the role played by implicit gender stereotypes remains robust when varying the magnitude of the monetary incentives for employing a more productive worker. If financial incentives prove effective in countering the contribution of implicit gender bias, then offering higher rewards to employers could emerge as a potential solution to diminish gender discrimination.

Additionally, social considerations, stemming from employers not solely pursuing self-interest but also caring about the impact of their choices on employees, could either displace or counterbalance unconscious bias in employment decisions. We address this eventuality by considering two types of employment decisions: hiring and career advancement. Our hypothesis posits that hiring decisions carry a heightened social concern as one candidate gains a payoff while the other receives nothing. In contrast, promotion decisions may allow for more significant influence from implicit motivations because, even though one candidate benefits more, the other still receives a positive payoff. Access to the labor market represents only the first stage where gender based discrimination may affect women's working opportunities, income and, in turn, life satisfaction. Career advancement decisions may also be affected by the same biases, contributing to a gender leadership gap. The existing evidence suggests that women are likely to be discriminated against in higher-status jobs, particularly in male-dominated fields (for a review of the literature, see Riach and Rich, 2006; Azmat and Petrongolo, 2014; Bertrand and Duflo, 2017). Thus, if the role of implicit gender bias is stronger in promotion decisions, policy interventions aimed at establishing gender equality of opportunities in the labour market should target especially these decisions.

Lastly, a noteworthy aspect of Coffman et al. (2021) study design is the inclusion of a control condition wherein the *same* workers are identified by their month of birth rather than their gender. This condition proves valuable in assessing whether implicit gender stereotypes influence hiring decisions even when the gender dimension is not explicitly disclosed but can be deduced, based on preconceived gender stereotypes, through information on the workers' ability distribution.

We answer our research questions by collecting our data in two steps. In one preliminary study (the IAT survey), we collect an appropriate measure of stereotypes using the Gender-Science Implicit Association Test (IAT).[2] This test is a computer-based tool developed by social psychologists (Greenwald et al., 1998) that exploits the reaction time to associations between male or female names and scientific or humanistic fields. The underlying assumption is that responses are faster and more accurate when gender and field subjects are more closely associated by the individual (Lane et al., 2007).

Then, we collect data through a survey experiment where participants (employers) have to decide which of two workers they want to hire/promote. The two workers (selected in a preliminary study) are defined by their gender (or month of birth) and the employer, at the time of the decision, has information about ex-ante (easy quiz) performance but is uncertain about the worker's ex-post (hard quiz) performance, that will determine her/his payment. While for hiring decisions employer's earnings depend only on the hard quiz performance of the hired worker, for promotion decisions employers have to decide which worker will be Rank A and which worker will be Rank B and they are paid based on the unknown hard-quiz performance of both workers.[3]

We document that implicit associations, measured by the IAT, explain employment decisions, both in terms of access to the labour market and in terms of career advancements. In both types of decision, when having to choose between a female and a male worker with the same ex-ante ability, the higher the male-science implicit association of the employer, the higher her/his likelihood of hiring/promoting a male for sure and the lower her/his likelihood of leaving the decision to chance. The option to leave the hiring decision to chance was introduced by Coffman et al. (2021) with the aim of allowing for expressions of indifference; the availability of this option should increase the likelihood that choosing one of the other two groups reflects a strict preference. Since in the data considered employers choose between two workers with the same ex-ante performance, it is not surprising that, on average, about 70% of them decides to leave the employment decisions to chance. Our evidence of a negative effect of higher male-science implicit association on the decision to leave the choice to chance reveals that unconscious bi-

---

[2] Further information for this preliminary study can be found in Section 2.1.

[3] Régner et al. (2019) examines the effect of explicit and implicit gender biases on promotion decisions made by scientific evaluation committees, instead of single individuals, for elite research positions and finds that committees with strong implicit gender biases promote fewer women if they do not believe that external barriers hold women back.

ases induce to reveal strict preferences outweighing possible image concerns or social desirability biases.

Enhancing incentives for employing more productive workers seems to mitigate the impact of implicit gender-science associations on hiring decisions. However, this reduction in the effect lacks statistical significance, indicating that unconscious bias influences these choices regardless of the size of employers' monetary incentives. Conversely, when the gender of the worker remains undisclosed, with employers solely aware of the ability distribution within worker groups, implicit gender stereotypes cease to factor into hiring and career advancement determinations. This suggests that these stereotypes may not be as deeply ingrained as to lead employers to associate specific genders with worker abilities based on preconceived notions. Furthermore, our findings reveal that the influence of unconscious bias remains consistent across gender, age, and income, underscoring its persistent nature.

We also measure and study the role of self-reported (i.e. explicit) gender bias finding that overall it has no effect on both hiring and promotion decisions. It only reduces the likelihood of leaving the hiring decision to chance when the employer has high incentives. Similarly to Carlana (2019), we find that IAT scores do not correlate with self-reported gender bias, maybe because there is social desirability bias in the explicit answers (Greenwald et al., 2009).

Our work contributes to the growing debates in social psychology (see for instance McConnell and Leibold, 2001; Nosek et al., 2007; Blanton et al., 2009; Oswald et al., 2013), and in economics (see for instance Rooth, 2010; Reuben et al., 2014; Glover et al., 2017; Corno et al., 2019; Carlana, 2019; Gioia and Immordino, 2023) on what is measured by the Implicit Association Test and on its predictive power of actual behavior.

The papers most closely related to our research are Rooth (2010) and Reuben et al. (2014). While Rooth (2010) offers empirical evidence of ethnic discrimination in hiring, specifically against Arab-Muslim men compared to Swedish men using the IAT, our study differs in its focus on gender discrimination.

Similarly, Reuben et al. (2014) investigates the impact of gender-science stereotypes on hiring decisions, but our research distinguishes itself by exploring other factors that may override these stereotypes. We particularly delve into the role of increased monetary incentives for hiring more productive workers, examine differences in how gender stereotypes influence various employment decisions (hiring vs. career advancement), and assess whether these stereotypes still affect hiring choices even when gender is not explicitly disclosed but can be inferred. Additionally, our adoption of the design from Coffman et al. (2021) uncovers an intriguing aspect not addressed in Reuben et al. (2014): the correlation between the IAT and the likelihood of leaving hiring and promotion decisions to chance.

Finally, in a replication of Coffman et al. (2021), Gioia and Immordino (2023) found initial discrimination against women when presented as low-performing individuals but a reversal in favor of women when their gender was disclosed, thus confirming Coffman et al. (2021) findings. This pro-women bias occurred with both male and female employers and was more pronounced when employers were women. However, it disappeared when higher monetary incentives were offered for hiring more productive workers.

The remainder of the paper is organized as follows. Section 2 describes our experimental design and the data. Section 3 presents the results and Section 4 concludes the paper.

2. Experimental design and data

Our experiment is composed by four surveys. Before running the main experimental survey on employment decisions (hereafter the gender-employment survey), we conducted two preliminary studies: the first has been used to collect information on our main explanatory variable (implicit gender-science association) and the second to collect performance information on a sample of subjects used as workers in the gender-employment survey. Besides the gender-employment survey, we have also conducted a month-of-birth-employment survey (hereafter the month-employment survey). All surveys have been conducted on Prolific Academic using the survey software Qualtrics. In this section we describe in detail the first three surveys and present the data collected and used in the analysis. We will devote Section 3.3 to the month-employment survey.

2.1. Implicit Association Test survey

Previous research has shown that the Implicit Association Test (Greenwald et al., 1998) is a powerful and flexible measure of unconscious attitudes and beliefs, including gender prejudices and stereotypes (Rudman et al., 1999, 2001).[4] Thus, before conducting the gender-employment survey, in a preliminary study we collected information on

---

[4] As pointed out by Carpenter et al. (2019), the IAT is not a measure of "attitudes" or "bias"; it measures mental associations that often, although not always, predict cognition and behavior (Greenwald et al., 2009), especially uncontrolled behavior (Friese et al., 2009).

implicit measures of gender-science stereotype endorsement by asking participants to complete an IAT associating sex with science-related abilities.

The IAT is a computer-based behavioral measure in which subjects are asked to rapidly place words (and/or pictures) displayed on their screen into categories. It assesses response latency and accuracy by interpreting easier pairings (as indicated by faster responses) as having a stronger automatic cognitive association than more difficult pairings (as indicated by slower responses). Thus, the advantage of using the IAT instead of self-reported measures is that it does not rely on respondents' ability or willingness to report their attitudes (Greenwald and Banaji, 1995; Dovidio and Fazio, 1992) thus avoiding individuals' tendency to censor or bias their answer for social desirability concerns (Swim et al., 1995).

We have elicited the IAT in a preliminary survey and not as a task of the employment surveys for two reasons. First, we wanted participants in the gender-employment survey and in the month-employment survey to have similar gender stereotypes as measured by implicit gender-science associations. By preliminary measuring unconscious attitudes, we were able to randomize participants to the two experiments. Second, we wanted to shorten the employment surveys to maximize participants attention. The drawback of this choice is that we had to recruit a bigger sample in the preliminary IAT study to take into account attrition. However, thanks to the randomization, we expected a similar attrition rate both in the gender-employment survey and in the month-employment survey.

We ran a survey-based IAT using the web-based tool that allows to create IAT via on-screen menus and that provides a downloadable ready-to-run Qualtrics IAT survey (Carpenter et al., 2019). Following Nosek et al. (2002), we used *Male, Man, Boy, Brother, He, Him, His, Son* as stimuli of the target "Male" and *Female, Woman, Girl, Sister, She, Her, Hers, Daughter* as stimuli of the target "Female". As regards the categories, "Science" had as stimuli *Chemistry, Physics, Biology, Biophysics, Engineering, Astronomy, Biochemistry, Neuroscience* and "Liberal arts" had *Philosophy, Arts, Humanities, History, Spanish, English, Latin, Music* (see Figure 3 in Appendix A).

In order to counterbalance left/right starting positions of targets and categories, there were four left/right permutations and one of them was randomly assigned to each participant (Nosek et al., 2005). In line with Greenwald et al. (2003) participants completed the gender-science IAT task in seven blocks (B1-B7): five practice blocks[5] and two critical blocks.[6] Table A1 in Appendix A displays the position of targets and categories in each block for each of the four permutations.

Participants received initial instructions including a table with the stimuli associated with each target and category and detailed instructions before starting each block (Carpenter et al., 2019). They observed a screen where a word appears and were asked to respond rapidly by pressing a right-hand key if the word corresponded to one target or category (e.g., “Male” and “Liberal arts”) and a left-hand key if the word corresponded to the other target or category (e.g., “Female” and “Science”). In each trial, the participant received immediate feedback and was forced to enter the correct answer in order to continue. Also, in order to facilitate correct performance, the words indicating the target and its stimuli appeared on the computer screen in a color, while the words of the category and its associated stimuli appeared on the computer screen in another color. Figures 4-7 in Appendix A provide sample screenshots of the IAT.

The IAT score of each subject has been computed according to the scoring algorithm described in Greenwald et al. (2003). First, we scored as missing all trials over 10,000 ms and dropped any IAT data from participants with $>$ 10% of responses with a latency lower than 300 ms. Second, we calculated within-person mean difference in response times, one for practice combined blocks (blocks 3 + 6) and one for the critical combined blocks (blocks 4 + 7). Third, we computed the standard deviation in response times for all trials in blocks 3 and 6, and for all trials in blocks 4 and 7. Fourth, we divided the two mean differences by the respective standard deviation generating two standardized difference scores (D-score) per participant. Finally, we averaged the two scores and created a single D-score.

A D-score of 0 indicates no difference in speeds; a positive score indicates that one was faster in the compatible block (where "Males" and "Science" where displayed on the same side and "Females" and "Liberal Arts" on the opposite side) meaning that

---

[5] B1 and B2 included 20 trials and had only targets and only categories, respectively; B5 included 40 trials having the targets displayed in the opposite side compared with previous blocks and served to wash out the left/right association learned in the previous blocks. B3 included 20 trials using both targets and categories combined following the left/right assignment of B1 and B2; B6 included 20 trials with the targets in their reversed position. A trial is deemed to be the time from when the target appears onscreen until the stimulus is correctly categorized.

[6] B4 and B7 included 40 trials with targets and categories displayed in the same position as in B3 and B6, respectively.

s/he associates male with science and female with liberal arts; a negative score indicates that one was faster in the incompatible block ("Males" - "Liberal Arts" *vs* "Females" - "Science") that is s/he associates female with science and male with liberal arts. Thus, a positive score is interpreted as reflecting an implicit sex-science stereotype such that males are seen as more capable in these fields.

We collected 400 observations and 6 were dropped because subjects spent less than 300 ms in more than 10% of responses. The remaining 396 subjects were randomly divided into two groups: one group (197 subjects) was invited to take part to the gender-employment survey; while the second group (197 subjects) was invited to take part to the month-employment survey aimed at testing the robustness of the findings. Here we will focus on the first group and the gender-employment survey. We will present data on the second group in Section 3.3.

The average D-score of the 197 *invited* participants was 0.321, ranging from -0.235 to 1.117, while the average D-score of the 100 *actual* participants (respondents) was 0.338, ranging from -0.20 to 1.117. Figure 1 shows the distribution of D-scores both for the invited sample and for the sub-sample of 100 subjects who responded. Vertical lines indicate the thresholds for different levels of bias based on the standard categorization of IAT scores by Greenwald et al. (2009).[7] According to this metric, D-scores in Figure 1 suggest that respondents generally hold pro-male biases. A two-sample Kolmogorov–Smirnov test for equality of distribution functions (p-value=0.996) and an Epps-Singleton two-sample empirical characteristic function test (p-value=0.951) confirm the absence of significant differences in the D-score between the two groups (i.e. invited and respondents).

---

[7] No bias if the score is between -0.15 and 0.15, slight bias for values between $|0.15|$ and $|0.35|$ (pro-male for positive values and pro-female for negative values), moderate bias between $|0.35|$ and $|0.60|$, and strong bias for scores higher than $|0.60|$.

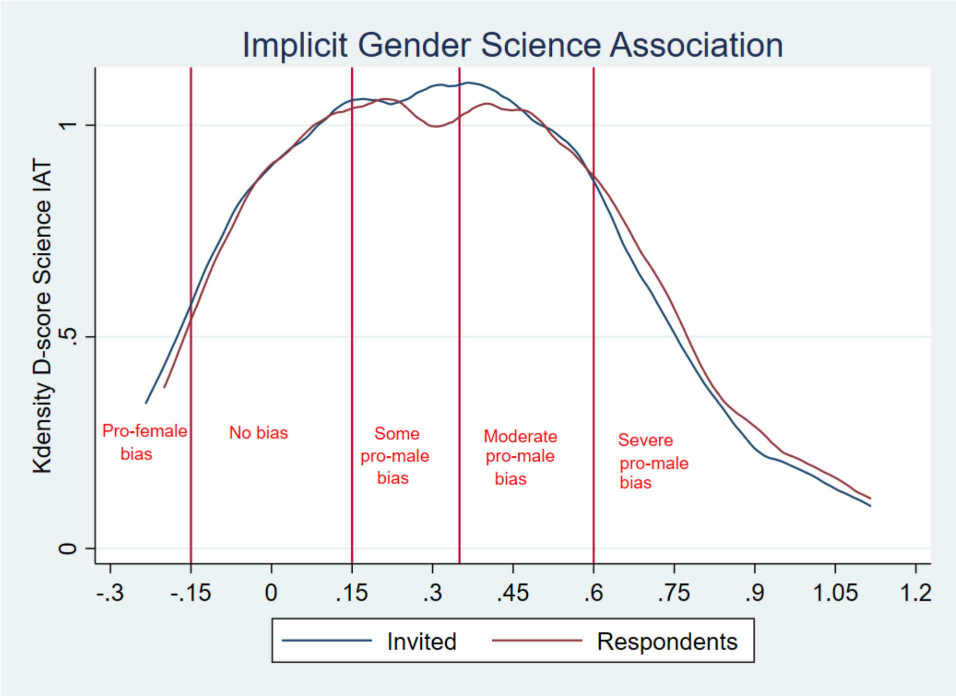


Figure 1: **Distribution of the Gender-Science IAT D-score**

After completing the IAT, subjects were asked to answer a short questionnaire with, among the others, two questions to elicit explicit gender-bias. The questions presented in thermometer format requested separate judgments for the IAT's two categories (Science and Liberal Arts) on a 7-point scale for the IAT's target dimension (Male and Female). The questions were as follows: "Please rate how much you associate the following domains with males or females" (the domains were Science and Liberal Arts). The set of options were: strongly female, moderately female, slightly female, neither male or female, slightly male, moderately male, strongly male. Scoring these seven options, respectively, as 1–7, the thermometer score was computed as the numerical difference between the two responses: higher values of the thermometer indicate stronger association of science with males rather than females (Nosek et al., 2005).

Figure 2 shows the distribution of the Thermometer for the sample of 197 invited subjects and for the sub-sample of 100 subjects who responded. A two-sample Kolmogorov–Smirnov test for equality of distribution functions (p-value=0.943) and an Epps-Singleton two-sample empirical characteristic function test (p-value=0.703) both confirm that the two distributions are not statistically different.[8]

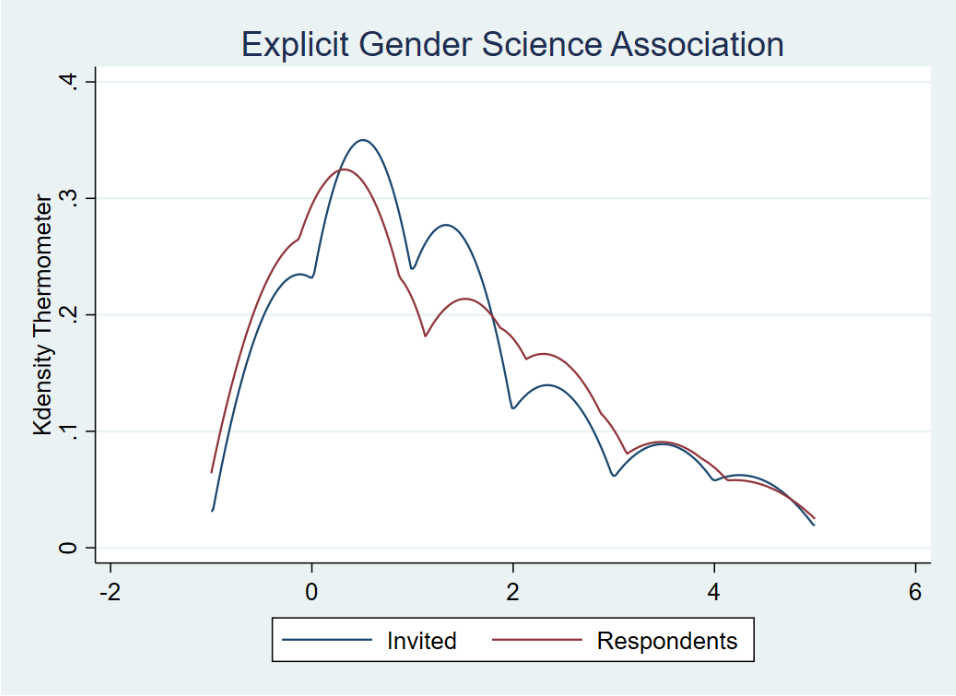


Figure 2: **Distribution of the Thermometer**

Explicit and implicit bias indicators are positively but weakly correlated in the sample of invited participants (corr=0.156, p-value=0.026, as in Greenwald et al. (2003)) and become not significantly correlated in the subsample of respondents (corr=0.039, p-value=0.702, as in Carlana (2019)).

2.2. Gender-employment survey

As in Coffman et al. (2021), before conducting our main survey on employment decisions, we ran a preliminary study aimed at obtaining indicators of performance for a pool of workers to be used in the employment decisions of the employment surveys. We asked few questions including the month of birth, separately to a female and a male pool. We recruited 150 people for each survey. Then, we restricted our attention to two groups of workers: male workers born in odd months (79) and female workers born in even months (69).[9] These two groups of workers were invited to complete two quizzes:

---

[8] Since the sample of 394 survey respondents has been randomized in two groups of 197 respondents to be used in the employment and in the month-employment survey, respectively, the distribution of the thermometer is similar in the two groups.

[9] We created two groups of workers each with the same gender and month of birth in order to use the same workers in the month-employment survey.

an easy and a hard math quiz, each consisting in 10 multiple-choice questions. Workers had three minutes (per quiz) to answer as many questions as possible and received, for one randomly selected quiz, a bonus payment of 10 cents for each question answered correctly. Workers were made aware that their performances could have been shown to other participants in a follow-up experiment. In total, we recruited 105 workers (52 females and 53 males). On average, males answered correctly 6.47 questions of the easy quiz (ranging from 3 to 10) and females 5.67 (ranging from 0 to 9).

The performances collected in this preliminary survey were used to ask participants to the gender-employment survey, "employers", to make incentivized employment decisions over available workers. Indeed, in the gender-employment survey we elicited employment decisions in a controlled environment mimicking real-world job market along three dimensions: (i) employers receive information on an initial measure of candidate's performance (easy quiz performance) that serves as signal of the candidate's capacity to perform well in the job for which s/he is hired or promoted; (ii) the employer's payoff depends on the actual performance on the job of the selected candidate (that is the hard quiz performance, unknown to employers at the time of the decision), thus the employer has an incentive to select the best candidate; (iii) in hiring decisions the employer's payoff depends only on the hired worker while in promotion decisions the employer's payoff depends on both workers but the marginal return is higher for the promoted worker.

The gender-employment survey is divided into three parts. The first two parts follow the procedure implemented by Coffman et al. (2021) to elicit prior and posterior beliefs and to study hiring decisions. Instead, the third part uses the same setting to study promotion decisions. At the end, subjects completed a short questionnaire. Experimental instructions are reported in the online appendix. To incentivize decisions, on top of the fixed show-up fee, the employer earns a bonus: one of the three parts and one of the decisions taken in that part are randomly selected and the employer earns money based on the hard-quiz performance of the selected worker in the decision that counts.

In Part 1 of the study we explain participants that they were going to make choices between individuals who completed a previous study where they answered to two quizzes (one easy and one hard) and that, in order to help them making these decisions, we would have shown the easy quiz performance while basing their bonus payment on the hard quiz performance. First, we give extensive instructions on how to understand the content displayed in the form of a bar chart. Then, we elicit employers' prior beliefs about the performance gap between male and female workers.[10] After prior-beliefs elicitation, the employer is asked to make nine hiring decisions based on performance information of workers provided in the form of a bar chart comparing the distribution of male and female workers.[11] In each decision, the employer has to choose whether to hire a female worker, a male worker or let chance determine who is hired (in this case the computer randomly determines which group to hire from). If one of these decisions is randomly selected as the decision that counts for payment, one worker from the selected group is chosen at random to be hired. The hired worker receives an additional 25 cents as bonus payment and the employer receives 10 cents for each question answered correctly by the hired worker on the hard quiz in the decision randomly selected for payment. At the end of Part 1, we elicited posterior beliefs using the same questions of prior beliefs elicitation.

In Part 2 employers are asked to make two sets of nine hiring decisions between specific pairs of workers. For each hiring decision, employers have information on the exact performance that each of the two workers obtained on the easy quiz. The displayed performance for the female and the male worker in the pair for each decision are: four versus four; five versus four; six versus four; seven versus four; eight versus four; six versus six; seven versus six; eight versus six; eight versus eight. Thus, in three of the hiring decisions, the available workers have the same performance on the easy quiz while in the other six decisions the male worker has a weaker performance than the female worker. Employers could choose whether to hire the male worker, the female worker or to let chance determine who is hired.

Unconscious bias, as measured by implicit gender-science association, may be reinforced or diluted by the monetary incentive associated with the decision. On one hand, lower incentives may make social pressure and social desirability concerns more salient, thus weakening the role of unconscious bias in the adopted decision making criteria. On

---

[10] The question used to elicit beliefs was the same used in Coffman et al. (2021): "If you compare the average score of a male (*odd-month* in the month-employment survey) worker to the average score of a female (*even-month*) worker from round 1 of the math questions, what do you think the difference in scores would be?". The same question was used for round 2 (hard quiz) and both questions were used also for the posterior beliefs.

[11] As in Coffman et al. (2021), all employers make the same nine hiring decisions. The distributions of the first eight decisions are formed considering subsets of workers born during different date ranges and the order in which such decisions appear is randomized at the participant level. The last decision is the same for all participants and contains the distributions of the full set of male and female workers, respectively.

the other hand, unconscious bias may play a stronger role in the decision making process when incentives are lower if the individual is more likely to follow "rules of thumb" to simplify a decision with a low marginal return. In order to investigate the role of incentives as moderators of unconscious bias in hiring decisions, employers faced two screens with the same nine hiring decisions. In the first screen, the incentive was as in Part 1. Instead, if one of the decisions belonging to the second screen was randomly selected for payment, employer's incentive was higher as s/he could receive, as an additional bonus payment, 50 cents (instead of 10) for each question answered correctly by the hired worker on the hard quiz in the selected decision.

In Part 3 of the gender-employment survey, employers are asked to make nine promotion decisions. They receive information on the performance obtained by the pair of workers in the easy quiz as in Part 2. They have to decide to which worker to assign Rank A and the other will be assigned Rank B. As in Part 2, they have the opportunity to assign Rank A to a particular female worker, a particular male worker, or have chance determine the worker with Rank A. If they choose to let chance determine the worker with Rank A, then there will be a 50% chance that the Rank A worker will be the female worker and a 50% chance that the Rank A worker will be the male worker. If Part 3 is randomly selected for payment, Rank A worker receives 1 dollar and Rank B worker receives 25 cents. The employer receives as an additional bonus payment 50 cents for each question answered correctly on the hard quiz by the Rank A worker in the selected decision and 10 cents for each question answered correctly on the hard quiz by the Rank B worker in the selected decision.

2.3. Data

We recruit 100 employers. Table 1 shows the descriptive statistics of our sample restricting attention to the three decisions in which employers choose between workers with the same easy quiz performance. We study employers' decisions by means of four dependent variables: *Female&Chance* is computed coding it 1 if a female worker is selected intentionally, 0.5 if chance determines who is selected, and 0 if a male worker is selected intentionally as in Coffman et al. (2021); *Female* is a dummy variable taking the value of 1 if a female worker is selected intentionally and 0 otherwise; *Chance* takes the value of 1 if the employer chooses to leave the decision to chance and 0 otherwise, and *Male* is a dummy variable for the probability with which a male worker is selected intentionally.

Table 1: Descriptive Statistics

	Mean *(1)*	**Std. dev.** *(2)*	**Min** *(3)*	**Max** *(4)*
PANEL A: Hiring low incentive				
Female&Chance	.478	.275	0	1
Female	.13	.337	0	1
Chance	.697	.46	0	1
Male	.173	.379	0	1
PANEL B: Hiring high incentive				
Female&Chance	.453	.264	0	1
Female	.097	.296	0	1
Chance	.713	.453	0	1
Male	.19	.393	0	1
PANEL C: Promotion				
Female&Chance	.468	.262	0	1
Female	.107	.309	0	1
Chance	.723	.448	0	1
Male	.17	.376	0	1
PANEL D: IAT, Controls				
IAT Gender Science				
D-score	.338	.313	-.200	1.117
Discrete D-score	2.29	1.179	0	4
Thermometer	1.29	1.404	-1	5
Controls				
Posterior(easy gap)	2.69	2.86	-5	10
Posterior(hard-easy gap)	-.19	2.261	-12	8
No. of Obs.	300			

For the sake of clarity, we present the outcomes separately for each set of decisions. In Panel A, we consider the first set of decisions of Part 2 where employers had low incentives to make hiring decisions (10 cents for each question answered correctly by the hired worker on the hard quiz). We see that on average a female worker is hired, intentionally and by chance, in about 48% of the decisions[12] but in about 70% of choices employers leave the hiring decision to chance while a female is hired intentionally only with a probability of 13%. A male is hired intentionally in about 17% of decisions. When incentives are higher, Panel B, the probability of hiring a female intentionally is considerably lower (9.7%) and both the probability of leaving the decision to chance and, above all, the probability of selecting a male intentionally are higher (71% and 19%, respectively).

In Panel C we turn our attention to career advancement decisions. We see that on average a female is promoted in about 11% of decisions, a male is promoted 17% of the times and employers leave the decision to chance with a probability of 72%.

In Panel D, we report descriptive statistics for our measures of gender stereotypes and for the controls included in the regressions. The average *D-score* in the sample was 0.33, indicating on average a slight unconscious pro-male bias. In order to better take into account the distribution of D-score, we also created a categorical variables taking values from 0 to 4 for pro-female bias, no bias, slight pro-male bias, moderate pro-male bias and strong pro-male bias, respectively. The *Discrete D-score* is on average 2.29. Explicit gender-science associations were measured through the *Thermometer*, that is the numerical difference between the extent to which employers associate science and liberal arts with males (Nosek et al., 2005). The *Thermometer* ranges from -1 to 5 and is on average 1.29 in our sample, thus showing a pretty low explicit pro-male bias.

Finally, as in Coffman et al. (2021), we include among controls the employer's posterior belief — after observing the distribution of abilities in the easy quiz for the two groups of workers — of the average performance gap in the easy quiz, *Posterior (easy gap)*, which on average favors male workers (2.69) and a difference between the posterior belief of the average performance gap in the hard quiz and the posterior belief of the average performance gap in the easy quiz, *Posterior (hard–easy gap)*, which is on average close to zero (-0.19).

---

[12] If there is no discrimination (neither belief-based nor taste-based), in the observed decisions where workers have the same easy quiz performance, employers should hire female workers 50% of the time. As in Coffman et al. (2021), this is not the case also in our setting. In fact, employers hire female workers in 47.8% of decisions if there are low incentives and in 45.3% of decisions if incentives are higher; both figures are significantly below the 50% benchmark (p-value=0.087 and 0.001, respectively). The same holds true for promotion decisions, where employers promote females 46.8% of the times, significantly below the 50% benchmark (p-value=0.018).

3. Results

In this section, we present our main results. First, we discuss hiring decisions and study the role of increasing the monetary incentive to employ more productive workers. Then, we turn our attention to promotion decisions. Finally, we study whether implicit gender stereotypes play a role also when the gender dimension is not explicitly stated but may be inferred – based on held gender stereotypes – by the ability distribution of the two groups of workers.

3.1. Hiring

In this section we focus on hiring decisions. We consider the three decisions asking to choose between workers with the same easy-quiz payoff both for the low incentive and for the high incentive scenario. In all specifications we control for *Posterior(easy gap)*, *Posterior(hard-easy gap)*, decision fixed effects and cluster standard errors at the respondent's level.

In Table 2 we study the role of unconscious bias by using the continuous IAT score. In column 1, we estimate ordinary-least-squares regressions of the probability of hiring a female worker (both intentionally and by chance, as in Coffman et al. (2021)) over a male worker by employers who make hiring decisions between pairs of workers with the same easy-quiz performance. As this may mask important heterogeneity if unconscious bias differently affect the probability of *taking the responsibility* of selecting a female and the probability of leaving the final decision to chance, we also look separately at the probability that a female worker is hired intentionally (column 2), the probability that the employer leaves the decision to chance (column 3) and the probability that a male worker is hired intentionally (column 4).

Table 2: Continuous IAT Score and Hiring Decisions

	Female&Chance *(1)*	**Female** *(2)*	**Chance** *(3)*	**Male** *(4)*
PANEL A				
High Incentive	-0.025	-0.033*	0.017	0.017
	(0.020)	(0.020)	(0.024)	(0.027)
D-score	-0.063	0.073	-0.271**	0.198*
	(0.060)	(0.062)	(0.122)	(0.104)
Adjusted R-squared	0.028	0.006	0.035	0.048
PANEL B				
High Incentive	-0.033	-0.022	-0.022	0.044
	(0.024)	(0.019)	(0.037)	(0.039)
D-score	-0.074	0.090	-0.328**	0.238**
	(0.067)	(0.077)	(0.127)	(0.105)
D-score*High Incentive	0.023	-0.034	0.115	-0.081
	(0.061)	(0.054)	(0.082)	(0.089)
Adjusted R-squared	0.026	0.004	0.035	0.047
Controls	YES	YES	YES	YES
Decision FE	YES	YES	YES	YES
No. of Obs.	600	600	600	600

In all estimates standard errors (reported in parentheses) are corrected for heteroscedasticity and clustered at the respondent level. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Higher levels of the variable *D-score* represent stronger implicit association between males and science. In Panel A, we see that a stronger implicit association between males and science significantly reduces the probability of leaving the hiring decision to chance between workers with the same easy-quiz performance (column 3) and produces a statistically significant increase in the probability of hiring a male intentionally (column 4).[13] Thus, gender stereotypes operate by choosing males more often, while relying less often on chance. The fact that the probability of hiring a female is not affected could be interpreted as an unconscious attempt to hide (to oneself) socially misbecoming

---

[13] Our results hold if we estimate a Probit model for the dependent variables in columns 2-4.

stereotypes.

The dummy *High Incentive*, taking the value of 1 for decisions belonging to the high incentive scenario, significantly reduces the probability of hiring a female intentionally thus suggesting that employers change their hiring criteria when compensations based on the unknown hard-quiz performance of the chosen worker gets larger and, possibly, become less affected by image concerns and social desirability motives.

Our evidence on the role of unconscious bias could hide important heterogeneity if, for instance, unconscious biases are reinforced or diluted by the power of incentives associated with the hiring decision. Thus in Panel B we include, among our control variables, also the interaction between *D-score* and *High Incentive*. A positive (negative) and statistically significant value of the interaction coefficient would point to a stronger (weaker) effect of unconscious bias when the decisions are associated with higher individual earnings. In columns (3) and (4), we see that the interaction coefficient points in the opposite direction as compared to the *D-score*'s coefficient thus suggesting a lower role of unconscious gender bias when incentives are stronger. However, the interaction coefficients are never statistically significant thus we can conclude that unconscious bias represented by a stronger association between males and science affects employers' hiring decisions regardless of the proposed incentive. Results on *D-score* are confirmed.

In Table 3 we present the same estimates of Table 2 using, as an indicator of implicit association, a discrete variable taking values from 0 to 4 for pro-female bias, no bias, some, moderate and severe pro-male bias, respectively. Panel A confirms that a stronger bias significantly increases the probability of hiring a male intentionally: the shift from one level to the next towards a stronger male-science implicit association increases the probability of hiring a male intentionally by about 5 percentage points. Also, employers holding a stronger bias are less likely to leave the hiring decision to chance: a unitary increase in the level of bias reduces the probability of leaving the decision to chance by 7.2 percentage points. Implicit gender association does not significantly affect the probability of hiring a female intentionally. Panel B confirms that the employer's monetary incentives do not statistically significantly moderate the effect of unconscious bias on decisions.

Table 3: Discrete IAT Score and Hiring Decisions

	Female&Chance *(1)*	**Female** *(2)*	**Chance** *(3)*	**Male** *(4)*
PANEL A				
High Incentive	-0.025	-0.033*	0.017	0.017
	(0.020)	(0.020)	(0.024)	(0.027)
Discrete D-score	-0.013	0.023	-0.072**	0.049*
	(0.016)	(0.016)	(0.032)	(0.028)
Adjusted R-squared	0.026	0.008	0.035	0.044
PANEL B				
High Incentive	-0.037	-0.011	-0.052	0.063
	(0.041)	(0.031)	(0.059)	(0.064)
Discrete D-score	-0.016	0.028	-0.087***	0.059**
	(0.018)	(0.021)	(0.033)	(0.027)
Discrete D-score*High Incentive	0.005	-0.010	0.030	-0.020
	(0.019)	(0.016)	(0.022)	(0.026)
Adjusted R-squared	0.024	0.006	0.035	0.044
Controls	YES	YES	YES	YES
Decision FE	YES	YES	YES	YES
No. of Obs.	600	600	600	600

In all estimates standard errors (reported in parentheses) are corrected for heteroscedasticity and clustered at the respondent level. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Unconscious biases are complex to elicit but have the advantage of being reliable as respondents cannot easily counterfeit their outcomes. Conversely, explicit biases are measured by simple questionnaires but their outcomes are easily faked by respondents. As already said in Section 2.1, in our sample, as in Carlana (2019), explicit and implicit biases are not significantly correlated, maybe because there is social desirability bias in the explicit answers (Greenwald et al., 2009). Thus, in Table 4 we study the effect of explicit gender science association on hiring decisions by estimating the same specifications reported in Table 2 but including the variable *Thermometer* instead of the IAT score.[14]

Table 4: Explicit Gender Science Association and Hiring Decisions

	Female&Chance *(1)*	**Female** *(2)*	**Chance** *(3)*	**Male** *(4)*
PANEL A				
High Incentive	-0.025	-0.033*	0.017	0.017
	(0.020)	(0.020)	(0.024)	(0.027)
Thermometer	-0.018	-0.011	-0.015	0.026
	(0.014)	(0.014)	(0.029)	(0.025)
Adjusted R-squared	0.031	0.003	0.003	0.031
PANEL B				
High Incentive	-0.018	-0.055**	0.075**	-0.020
	(0.025)	(0.027)	(0.031)	(0.032)
Thermometer	-0.015	-0.019	0.007	0.012
	(0.013)	(0.017)	(0.030)	(0.023)
Thermometer*High Incentive	-0.006	0.017	-0.045**	0.028
	(0.013)	(0.014)	(0.019)	(0.018)
Adjusted R-squared	0.030	0.002	0.006	0.032
Controls	YES	YES	YES	YES
Decision FE	YES	YES	YES	YES
No. of Obs.	600	600	600	600

In all estimates standard errors (reported in parentheses) are corrected for heteroscedasticity and clustered at the respondent level. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A shows that explicit gender bias are not significant predictors of hiring decisions and that, given the explicit bias, employers are less likely to hire a female intentionally when their marginal compensation increases. In Panel B, where we include the interaction between *Themometer* and *High Incentive*, we see that, for the decision of hiring either a male or a female intentionally, the size of the incentive does not affect the explicit biases which are never statistically significant. Instead, while employers not holding explicit bias are significantly more likely to leave the decision to chance

---

[14] Results on D-score hold if we include it among controls.

when incentives are higher, this effect significantly reduces as the explicit male-science association increases (column 3).

Our results are robust when we include gender, age and income among controls. Also, the estimated effects of unconscious bias are not heterogeneous by gender, age and income earned (results not reported and available upon request). Finally, we have also used the other six decisions taken by employers to investigate whether unconscious bias plays a role also when females have a better ex-ante performance and we found that it does not (results not reported and available upon request).

3.2. Promotion

In order to have a complete picture of the role of unconscious bias on employment decisions, in this section we look at how it affects employers' choice of whom to promote. We follow the same approach used for hiring decisions and consider only decisions where both workers have identical easy-quiz performance: i.e. both workers are known to answer 4, 6, or 8 (out of 10) questions correctly on the easy quiz.

Results in Table 5 show that unconscious bias are highly predictive of promotion decisions: with both the discrete and the continuous measure, higher implicit association between males and sciences translates into lower likelihood of leaving the promotion decision to chance (column 3) and higher likelihood of promoting the male worker intentionally (column 4). The effects are similar in size to those emerging for hiring decisions. We also find evidence of a significant negative effect of D-score on the probability with which a female worker is promoted (both intentionally and by chance) (column 1) but the dissaggregated outcomes in columns (2) and (3) show that this is driven by a lower probability of leaving the decision to chance rather than by a reduction of the probability with which a female worker is promoted intentionally. As for hiring decisions, it seems that employers unconsciously attempt to hide (to themselves) socially unpleasing stereotypes.

Table 5: Gender Science Association and Promotion Decisions

	Female&Chance	**Female**	**Chance**	**Male**
	(1)	*(2)*	*(3)*	*(4)*
Continuous IAT Score				
D-score	-0.122*	0.046	-0.335***	0.289***
	(0.064)	(0.068)	(0.126)	(0.107)
Adjusted R-squared	0.011	-0.006	0.040	0.043
Discrete IAT Score				
Discrete D-score	-0.030*	0.013	-0.086***	0.074***
	(0.017)	(0.018)	(0.032)	(0.027)
Adjusted R-squared	0.008	-0.005	0.037	0.038
Explicit Gender Science Association				
Thermometer	-0.008	-0.020	0.023	-0.003
	(0.015)	(0.014)	(0.029)	(0.026)
Adjusted R-squared	-0.009	0.000	-0.010	-0.015
Controls	YES	YES	YES	YES
Decision FE	YES	YES	YES	YES
No. of Obs.	300	300	300	300

In all estimates standard errors (reported in parentheses) are corrected for heteroscedasticity and clustered at the respondent level. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

When studying the effect of explicit gender-science association on promotion decisions, we again find that employers' explicit bias has no significant effect.

All in all, our results suggest that unconscious biases measured through implicit association between science and males are significant predictors of employment decisions, both in terms of access to the labour market and in terms of career advancements. In both types of decision, when having to choose between a female and a male worker with the same ex-ante ability (as measured by the easy-quiz performance), the higher the male-science implicit association of the employer, the higher his likelihood of hiring/promoting a male intentionally instead of leaving the decision to chance.

3.3. Month of birth

In this section, we test whether unconscious gender bias is so strong to play a role on employment decisions even when the gender dimension is not explicitly reported but may be inferred – based on held gender stereotypes – by information on the ability distribution of workers' group of belonging. With this aim, we run a second experiment (the month-employment survey) where employers make the same decisions of the employers in the gender-employment survey but (the same) workers are labeled in terms of their birth month rather than in terms of their gender, as in Coffman et al. (2021).

Thus, employers in the month-employment survey see and choose among the same set of available workers with the same performance distribution. However, while in the gender-employment survey participants make hiring and promotion decisions between female and male workers, in the month-employment survey, participants make both types of employment decisions over workers born in even months (corresponding to female workers in the gender-employment survey) or in odd months (corresponding to male workers in the gender-employment survey).[15]

197 of the employers taking part in the IAT survey (and having a reliable measure of IAT) have been randomly assigned to be invited to the month-employment survey. Of them, 110 actually submitted their answers. Table B1 in Appendix B reports descriptive statistics of respondents to the month-employment survey.

The average D-score of the 197 invited participants was 0.28, ranging from -0.236 to 1.119.[16] The average D-score of the 110 subjects who took part in the month-employment survey was 0.247, ranging from -0.22 to 1.119. Two-sample Kolmogorov–Smirnov test for equality of distribution functions (p-value=0.906) and Epps-Singleton two-sample empirical characteristic function test (p-value=0.865) confirm the absence of significant difference in the D-score between the two groups (sample and subsample).[17] In Figure 8 in Appendix B we show the distribution of D-score for the samples of subjects invited and taking part in the month-employment survey.[18]

Table 6 and 7 show that, when employees are labeled with their month of birth, the employers' IAT score (and also their explicit bias) does not affect their hiring and

---

[15] Whereas the labels used to describe the available workers vary, the performances of the available workers do not, as described in Section 2.2.

[16] Two-sample Kolmogorov–Smirnov test for equality of distribution functions (p-value=0.213) and Epps-Singleton two-sample empirical characteristic function test (p-value=0.652) confirm the absence of significant difference in the D-score between the two groups of 197 invited participants to the employment and the month-employment survey, respectively.

[17] Also, in the subsample of respondents, the distribution of D-scores is not different between respondents to the gender-employment survey and respondents to the month-employment survey: two-sample Kolmogorov–Smirnov test for equality of distribution functions (p-value=0.103), Epps-Singleton two-sample empirical characteristic function test (p-value=0.276).

[18] Also, in Figure 9 in Appendix B we show the distribution of the thermometer in both samples.

promotion decisions.

Table 6: Month-employment survey. Hiring Decisions

	Female&Chance *(1)*	**Female** *(2)*	**Chance** *(3)*	**Male** *(4)*
Continuous IAT Score				
High Incentive	0.012	0.015	-0.006	-0.009
	(0.021)	(0.021)	(0.034)	(0.032)
D-score	-0.050	-0.013	-0.074	0.087
	(0.064)	(0.044)	(0.134)	(0.124)
Adjusted R-squared	0.071	0.003	0.057	0.080
Discrete IAT Score				
High Incentive	0.012	0.015	-0.006	-0.009
	(0.021)	(0.021)	(0.034)	(0.032)
Discrete D-score	-0.017	-0.004	-0.027	0.031
	(0.017)	(0.012)	(0.035)	(0.033)
Adjusted R-squared	0.073	0.003	0.059	0.082
Explicit Gender Science Association				
High Incentive	0.012	0.015	-0.006	-0.009
	(0.021)	(0.021)	(0.034)	(0.032)
Thermometer	-0.001	-0.001	0.000	0.001
	(0.016)	(0.010)	(0.028)	(0.028)
Adjusted R-squared	0.068	0.002	0.055	0.077
Controls	YES	YES	YES	YES
Decision FE	YES	YES	YES	YES
No. of Obs.	660	660	660	660

In all estimates standard errors (reported in parentheses) are corrected for heteroscedasticity and clustered at the respondent level. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table 7: Month-employment survey. Promotion Decisions

	Female&Chance *(1)*	**Female** *(2)*	**Chance** *(3)*	**Male** *(4)*
Continuous IAT Score				
D-score	0.039	0.055	-0.032	-0.023
	(0.068)	(0.065)	(0.130)	(0.116)
Adjusted R-squared	0.048	0.016	0.076	0.079
Discrete IAT Score				
Discrete D-score	0.014	0.023	-0.018	-0.006
	(0.019)	(0.018)	(0.035)	(0.032)
Adjusted R-squared	0.050	0.021	0.077	0.079
Explicit Gender Science Association				
Thermometer	-0.006	0.001	-0.014	0.013
	(0.019)	(0.021)	(0.033)	(0.029)
Adjusted R-squared	0.047	0.014	0.077	0.080
Controls	YES	YES	YES	YES
Decision FE	YES	YES	YES	YES
No. of Obs.	330	330	330	330

In all estimates standard errors (reported in parentheses) are corrected for heteroscedasticity and clustered at the respondent level. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

4. Concluding remarks

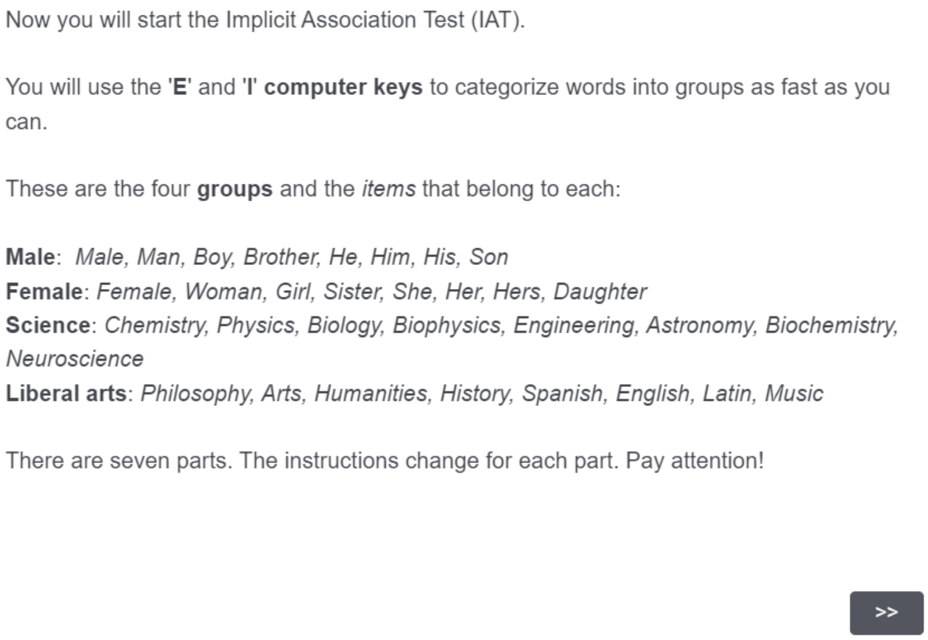
Our research demonstrates the utility of the IAT to predict behavior relevant for the labor market and the economy in general. Since implicit discrimination may be unintentional, policies aimed at affecting the behavior of human resources managers should differ from the ones thought to fight explicit discrimination. Managers could be informed about the existence of an implicit bias when hiring or promoting and could be asked to take the IAT, which has been shown to be a better indicator of stereotypes than explicit evaluation tests.

Once implicit associations have been measured, a possible policy would be to disclose them to recruiters. Alesina et al. (2018) studies the question of whether people change their behavior when they become aware of their stereotypes in the context of teachers' bias in grading immigrants and native children in middle schools. They find that teachers informed of their stereotypes increase grades assigned to immigrants and conclude that revealing stereotypes may decrease discrimination. However, since the disclosure of the IAT score may also induce a reaction from individuals who were not acting in a biased way, a more effective policy could be to select recruiters based on the result of the IAT and ensure that they adopt evaluation criteria fully based on task cues rather than on social ones. Such a policy would have pervasive effects since the influence of implicit bias on employment choices is not heterogeneous by gender, age or income earned.

Acknowledgements

We thank Lorenzo Pandolfi for useful discussions. The usual disclaimer applies.

Appendix A: IAT



Now you will start the Implicit Association Test (IAT).

You will use the '**E**' and '**I**' **computer keys** to categorize words into groups as fast as you can.

These are the four **groups** and the *items* that belong to each:

Male: *Male, Man, Boy, Brother, He, Him, His, Son*
Female: *Female, Woman, Girl, Sister, She, Her, Hers, Daughter*
Science: *Chemistry, Physics, Biology, Biophysics, Engineering, Astronomy, Biochemistry, Neuroscience*
Liberal arts: *Philosophy, Arts, Humanities, History, Spanish, English, Latin, Music*

There are seven parts. The instructions change for each part. Pay attention!

Figure 3: **Targets, categories and stimuli**

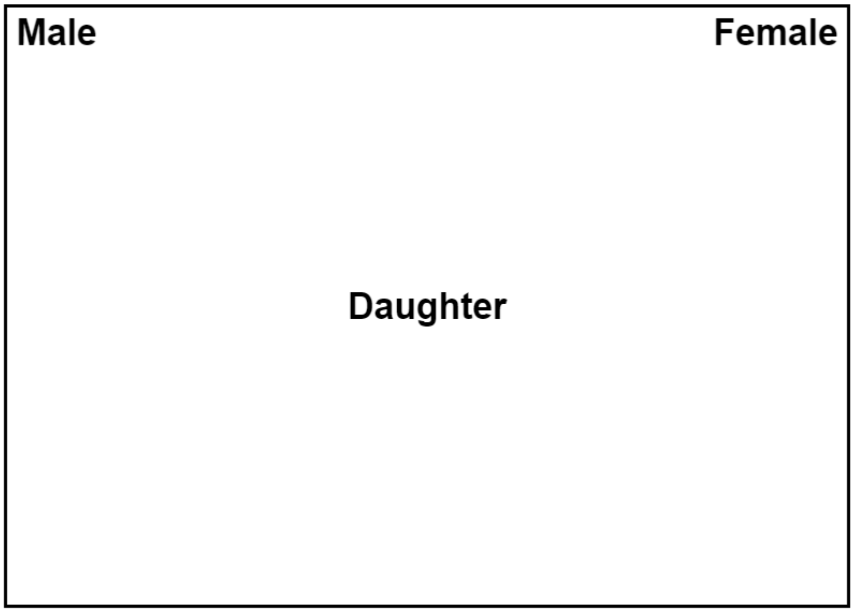


Figure 4: **Sample screenshot of the IAT**

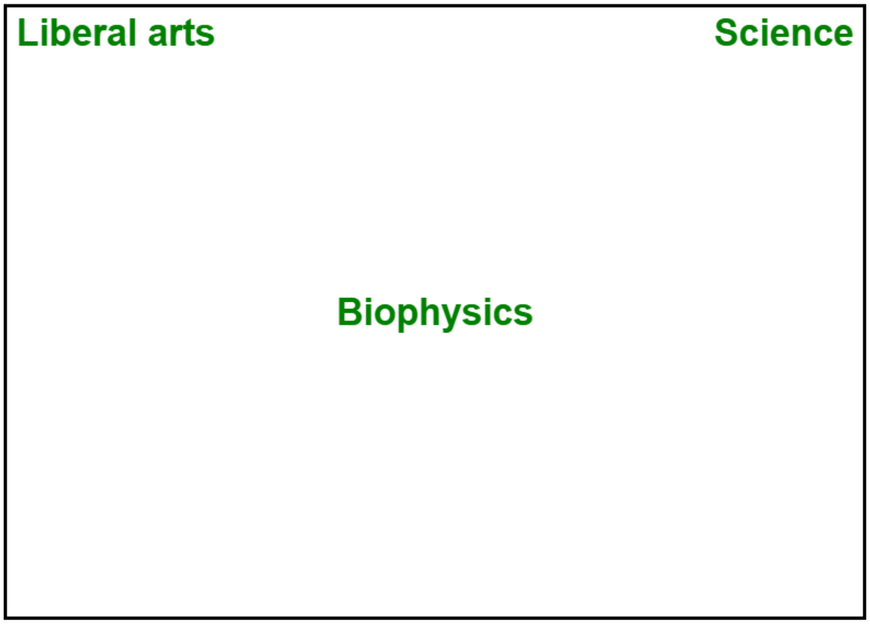


Figure 5: **Sample screenshot of the IAT (2)**

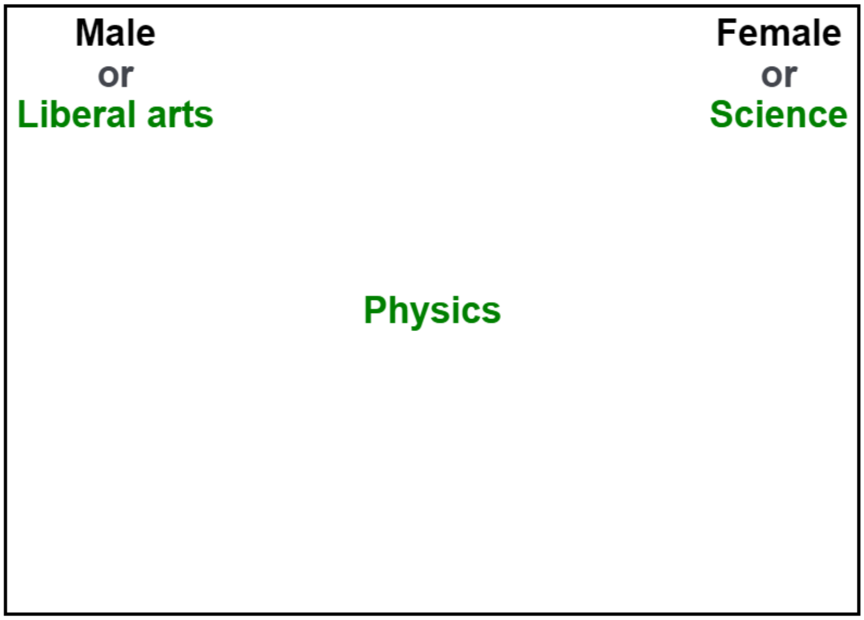


Figure 6: **Sample screenshot of the IAT (3)**

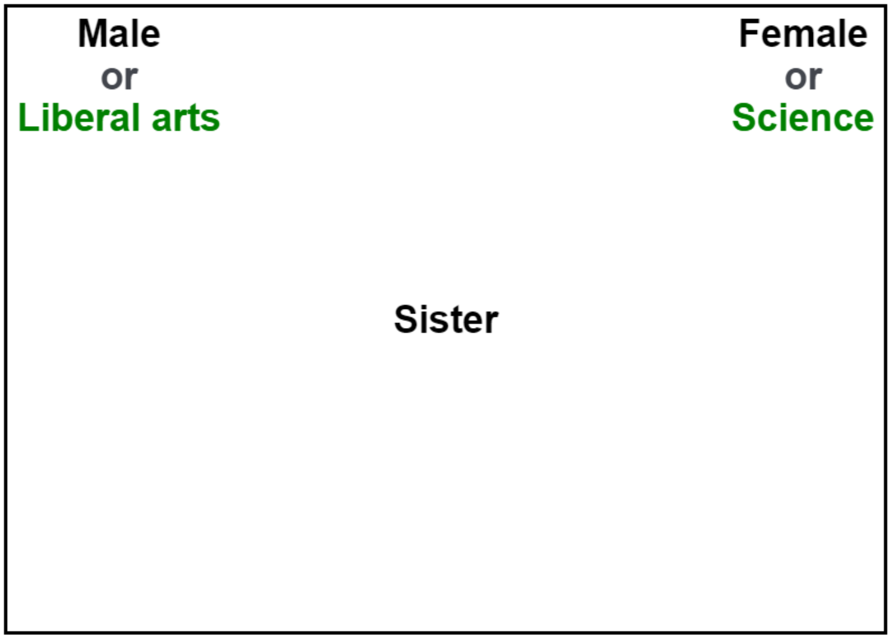


Figure 7: **Sample screenshot of the IAT (4)**

Table A1 displays the position of targets and categories in each block for each of the four permutations.

Table A1:Permutations and sequence of blocks in the IAT

Block *(1)*	Number of trials *(2)*	Purpose *(3)*	Left-key category-attribute *(4)*	Right-key category-attribute *(5)*
		PANEL A: Permutation 1		
1	20	Practice	male	female
2	20	Practice	science	liberal arts
3	20	Practice	male-science	female-liberal arts
4	40	Critical	male-science	female-liberal arts
5	20	Practice	female	male
6	20	Practice	female-science	male-liberal arts
7	40	Critical	female-science	male-liberal arts
		PANEL B: Permutation 2		
1	20	Practice	male	female
2	20	Practice	liberal arts	science
3	20	Practice	male-liberal arts	female-science
4	40	Critical	male-liberal arts	female-science
5	20	Practice	female	male
6	20	Practice	female-liberal arts	male-science
7	40	Critical	female-liberal arts	male-science
		PANEL C: Permutation 3		
1	20	Practice	female	male
2	20	Practice	science	liberal arts
3	20	Practice	female-science	male-liberal arts
4	40	Critical	female-science	male-liberal arts
5	20	Practice	male	female
6	20	Practice	male-science	female-liberal arts
7	40	Critical	male-science	female-liberal arts
		PANEL D: Permutation 4		
1	20	Practice	female	male
2	20	Practice	liberal arts	science
3	20	Practice	female-liberal arts	male-science
4	40	Critical	female-liberal arts	male-science
5	20	Practice	male	female
6	20	Practice	male-liberal arts	female-science
7	40	Critical	male-liberal arts	female-science

Appendix B: Month-employment survey

Table B1 reports descriptive statistics of respondents to the month-employment survey.

Table B1: Descriptive Statistics

	Mean *(1)*	**Std. dev.** *(2)*	**Min** *(3)*	**Max** *(4)*
PANEL A: Hiring low incentive				
Female&Chance	.332	.286	0	1
Female	.052	.221	0	1
Chance	.561	.497	0	1
Male	.388	.488	0	1
PANEL B: Hiring high incentive				
Female&Chance	.344	.295	0	1
Female	.067	.250	0	1
Chance	.555	.498	0	1
Male	.379	.486	0	1
PANEL C: Promotion				
Female&Chance	.405	.308	0	1
Female	.112	.316	0	1
Chance	.585	.493	0	1
Male	.303	.460	0	1
PANEL D: IAT, Controls				
IAT Gender Science				
D-score	.247	.302	-.221	1.119
Discrete D-score	1.982	1.146	0	4
Thermometer	1.136	1.464	-2	6
Controls				
Posterior(easy gap)	3.827	2.434	-3	10
Posterior(hard-easy gap)	-.282	1.671	-6	6
No. of Obs.	330			

Figure 8 shows the distribution of D-score in the samples of subjects invited and taking part in the month-employment survey.

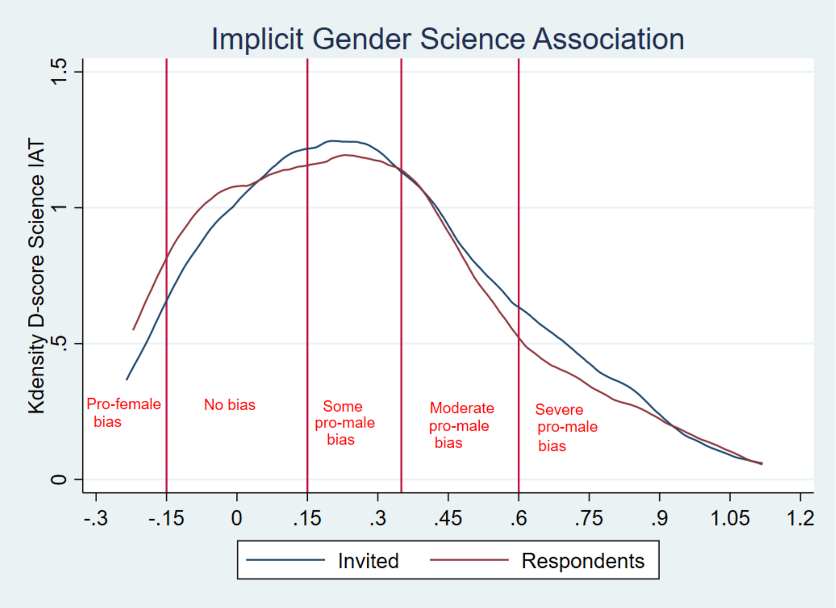


Figure 8: **Distribution of the Gender-Science IAT D-score in month-employment survey**

Figure 9 shows the distribution of the Thermometer in the samples of subjects invited and taking part in the month-employment survey.

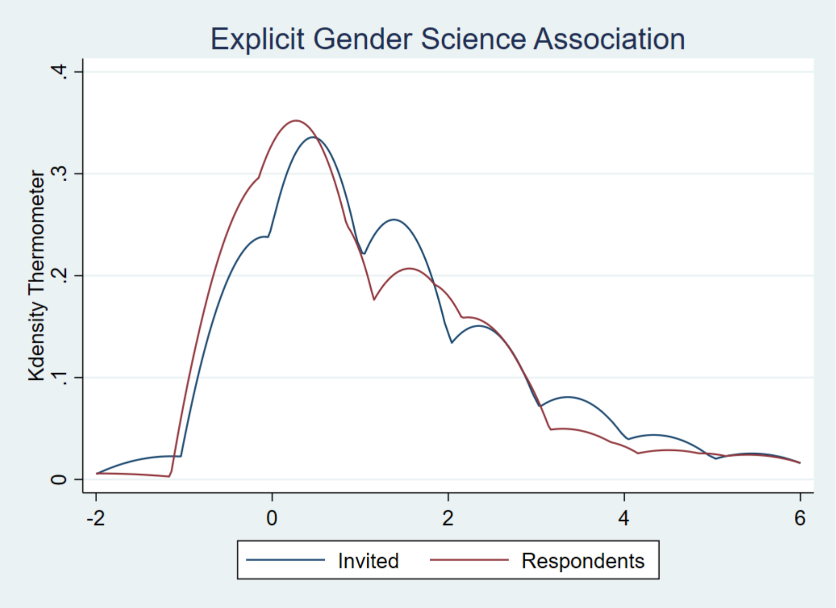


Figure 9: **Distribution of the Thermometer in month-employment survey**

References

Alesina, A., M. Carlana, E. La Ferrara, and P. Pinotti (2018). Revealing stereotypes: Evidence from immigrants in schools. Technical report, National Bureau of Economic Research.

Arrow, K. J. (2015). *The theory of discrimination*. Princeton University Press.

Azmat, G. and B. Petrongolo (2014). Gender and the labor market: What have we learned from field and lab experiments? *Labour Economics 30*, 32–40.

Becker, G. S. (1957). *The economics of discrimination*. University of Chicago press.

Bertrand, M. and E. Duflo (2017). Field experiments on discrimination. *Handbook of economic field experiments 1*, 309–393.

Blanton, H., J. Jaccard, J. Klick, B. Mellers, G. Mitchell, and P. E. Tetlock (2009). Strong claims and weak evidence: reassessing the predictive validity of the iat. *Journal of applied Psychology 94*(3), 567.

Bordalo, P., K. Coffman, N. Gennaioli, and A. Shleifer (2016). Stereotypes. *The Quarterly Journal of Economics 131*(4), 1753–1794.

Carlana, M. (2019). Implicit stereotypes: Evidence from teachers' gender bias. *The Quarterly Journal of Economics 134*(3), 1163–1224.

Carpenter, T. P., R. Pogacar, C. Pullig, M. Kouril, S. Aguilar, J. LaBouff, N. Isenberg, and A. Chakroff (2019). Survey-software implicit association tests: A methodological and empirical analysis. *Behavior research methods 51*(5), 2194–2208.

Coffman, K. B., C. L. Exley, and M. Niederle (2021). The role of beliefs in driving gender discrimination. *Management Science 67*(6), 3551–3569.

Corno, L., E. La Ferrara, and J. Burns (2019). Interaction, stereotypes and performance: Evidence from south africa. Technical report, IFS Working Papers.

Della Giusta, M. and S. Bosworth (2020). Bias and discrimination: what do we know? *Oxford Review of Economic Policy 36*(4), 925–943.

Dovidio, J. F. and R. H. Fazio (1992). New technologies for the direct and indirect assessment of attitudes. In *J. M. Tanur (Ed.), Questions about questions: Inquiries into the cognitive bases of surveys*, pp. 204–237. New York: Russell Sage Foundation.

Friese, M., W. Hofmann, and M. Wänke (2009). The impulsive consumer: Predicting consumer behavior with implicit reaction time measures. In *M. Wänke (Ed.), Social Psychology of Consumer Behavior*, pp. 335–364. New York, NY: Taylor Francis.

Gioia, F. and G. Immordino (2023). Incentives and gender discrimination. *forthcoming in the Journal of the Economic Science Association.*

Glover, D., A. Pallais, and W. Pariente (2017). Discrimination as a self-fulfilling prophecy: Evidence from french grocery stores. *The Quarterly Journal of Economics 132*(3), 1219–1260.

Greenwald, A. G. and M. R. Banaji (1995). Implicit social cognition: attitudes, self-esteem, and stereotypes. *Psychological review 102*(1), 4.

Greenwald, A. G., D. E. McGhee, and J. L. Schwartz (1998). Measuring individual differences in implicit cognition: the implicit association test. *Journal of personality and social psychology 74*(6), 1464.

Greenwald, A. G., B. A. Nosek, and M. R. Banaji (2003). Understanding and using the implicit association test: I. an improved scoring algorithm. *Journal of personality and social psychology 85*(2), 197.

Greenwald, A. G., T. A. Poehlman, E. L. Uhlmann, and M. R. Banaji (2009). Understanding and using the implicit association test: Iii. meta-analysis of predictive validity. *Journal of personality and social psychology 97*(1), 17.

Lane, K. A., M. R. Banaji, B. A. Nosek, and A. G. Greenwald (2007). Understanding and using the implicit association test: Iv: What we know (so far) about the method.

McConnell, A. R. and J. M. Leibold (2001). Relations among the implicit association test, discriminatory behavior, and explicit measures of racial attitudes. *Journal of experimental Social psychology 37*(5), 435–442.

Nosek, B. A., M. R. Banaji, and A. G. Greenwald (2002). Harvesting implicit group attitudes and beliefs from a demonstration web site. *Group Dynamics: Theory, Research, and Practice 6*(1), 101.

Nosek, B. A., A. G. Greenwald, and M. R. Banaji (2005). Understanding and using the implicit association test: Ii. method variables and construct validity. *Personality and Social Psychology Bulletin 31*(2), 166–180.

Nosek, B. A., F. L. Smyth, J. J. Hansen, T. Devos, N. M. Lindner, K. A. Ranganath, C. T. Smith, K. R. Olson, D. Chugh, A. G. Greenwald, et al. (2007). Pervasiveness and correlates of implicit attitudes and stereotypes. *European Review of Social Psychology 18*(1), 36–88.

Oswald, F. L., G. Mitchell, H. Blanton, J. Jaccard, and P. E. Tetlock (2013). Predicting ethnic and racial discrimination: a meta-analysis of iat criterion studies. *Journal of personality and social psychology 105*(2), 171.

Phelps, E. S. (1972). The statistical theory of racism and sexism. *The american economic review 62*(4), 659–661.

Régner, I., C. Thinus-Blanc, A. Netter, T. Schmader, and P. Huguet (2019). Committees with implicit biases promote fewer women when they do not believe gender bias exists. *Nature human behaviour 3*(11), 1171–1179.

Reuben, E., P. Sapienza, and L. Zingales (2014). How stereotypes impair women's careers in science. *Proceedings of the National Academy of Sciences 111*(12), 4403–4408.

Riach, P. A. and J. Rich (2006). An experimental investigation of sexual discrimination in hiring in the english labor market. *Advances in Economic Analysis & Policy 5*(2).

Rooth, D.-O. (2010). Automatic associations and discrimination in hiring: Real world evidence. *Labour Economics 17*(3), 523–534.

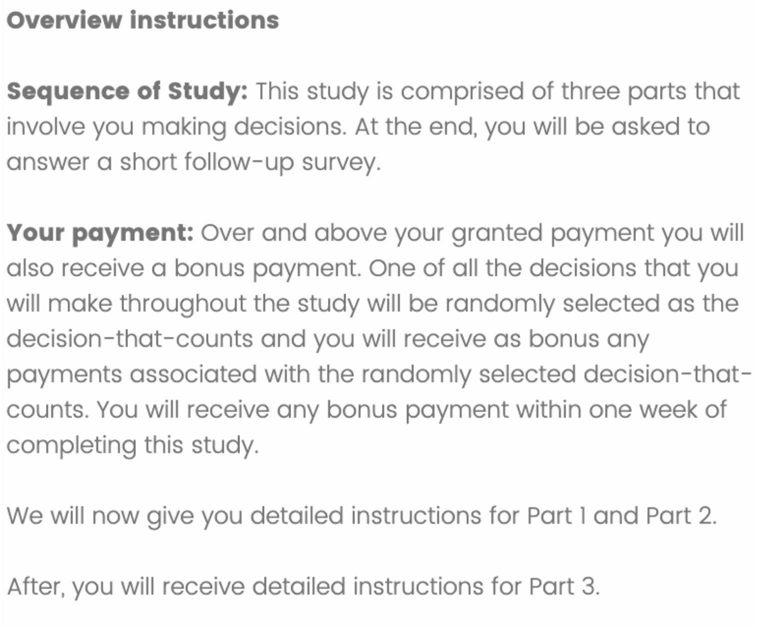
Rudman, L. A., A. G. Greenwald, and D. E. McGhee (2001). Implicit self-concept and evaluative implicit gender stereotypes: Self and ingroup share desirable traits. *Personality and Social Psychology Bulletin 27*(9), 1164–1178.

Rudman, L. A., A. G. Greenwald, D. S. Mellott, and J. L. Schwartz (1999). Measuring the automatic components of prejudice: Flexibility and generality of the implicit association test. *Social cognition 17*(4), 437–465.

Swim, J. K., K. J. Aikin, W. S. Hall, and B. A. Hunter (1995). Sexism and racism: Old-fashioned and modern prejudices. *Journal of personality and social psychology 68*(2), 199.

Full Instructions for Online Publication

The first figure shows the overview instructions displayed on respondents' screen after they gave their consent to participate in our study.



Overview instructions

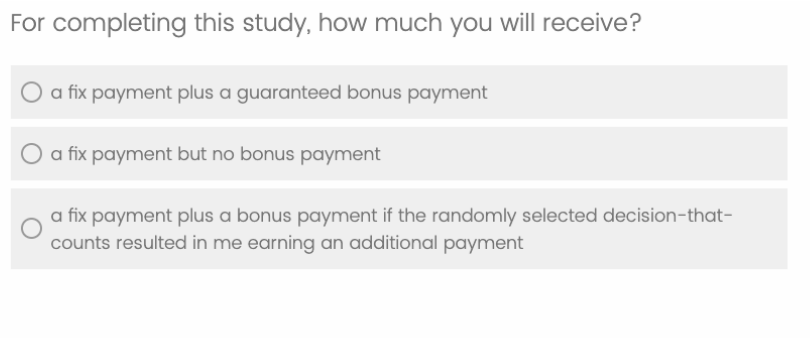
Sequence of Study: This study is comprised of three parts that involve you making decisions. At the end, you will be asked to answer a short follow-up survey.

Your payment: Over and above your granted payment you will also receive a bonus payment. One of all the decisions that you will make throughout the study will be randomly selected as the decision-that-counts and you will receive as bonus any payments associated with the randomly selected decision-that-counts. You will receive any bonus payment within one week of completing this study.

We will now give you detailed instructions for Part 1 and Part 2.

After, you will receive detailed instructions for Part 3.

After reading the overview instructions, participants had to answer correctly the following understanding question to proceed with the study.



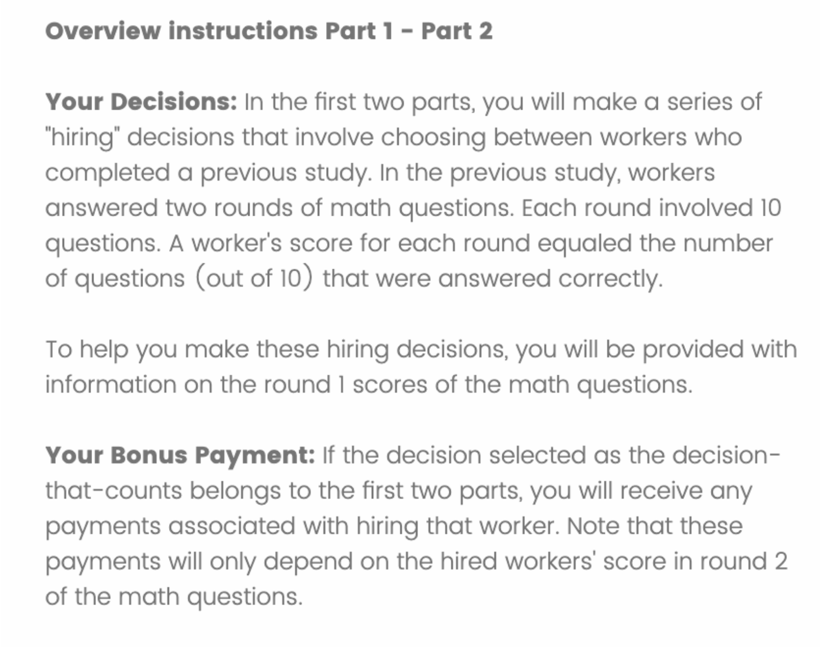
For completing this study, how much you will receive?

○ a fix payment plus a guaranteed bonus payment

○ a fix payment but no bonus payment

○ a fix payment plus a bonus payment if the randomly selected decision-that-counts resulted in me earning an additional payment

The next figures show how we inform participants that in the first two parts of the survey they will make a series of hiring decisions, how we give further information on participants payments for Part 1 and 2, and the corresponding understanding questions that must be answered correctly for the participant to proceed.

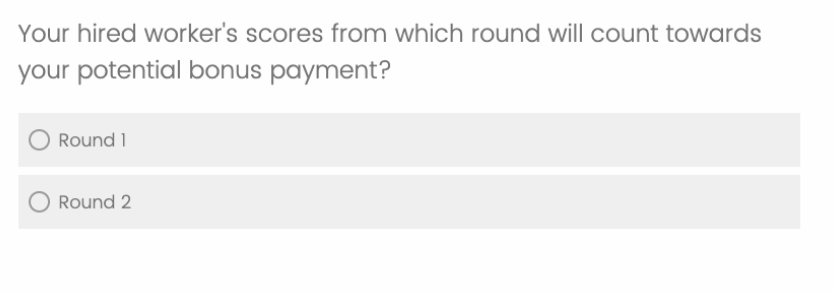


Overview instructions Part 1 - Part 2

Your Decisions: In the first two parts, you will make a series of "hiring" decisions that involve choosing between workers who completed a previous study. In the previous study, workers answered two rounds of math questions. Each round involved 10 questions. A worker's score for each round equaled the number of questions (out of 10) that were answered correctly.

To help you make these hiring decisions, you will be provided with information on the round 1 scores of the math questions.

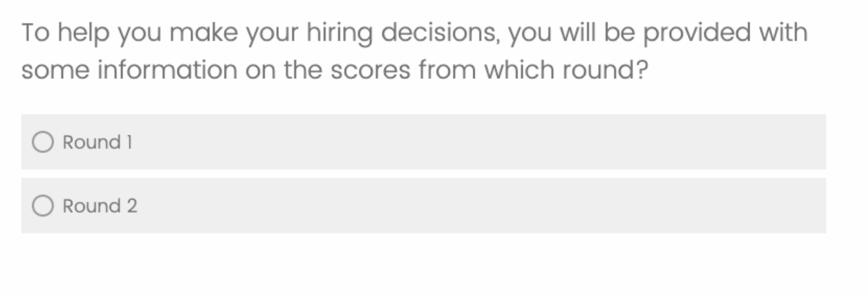
Your Bonus Payment: If the decision selected as the decision-that-counts belongs to the first two parts, you will receive any payments associated with hiring that worker. Note that these payments will only depend on the hired workers' score in round 2 of the math questions.



Your hired worker's scores from which round will count towards your potential bonus payment?

○ Round 1

○ Round 2

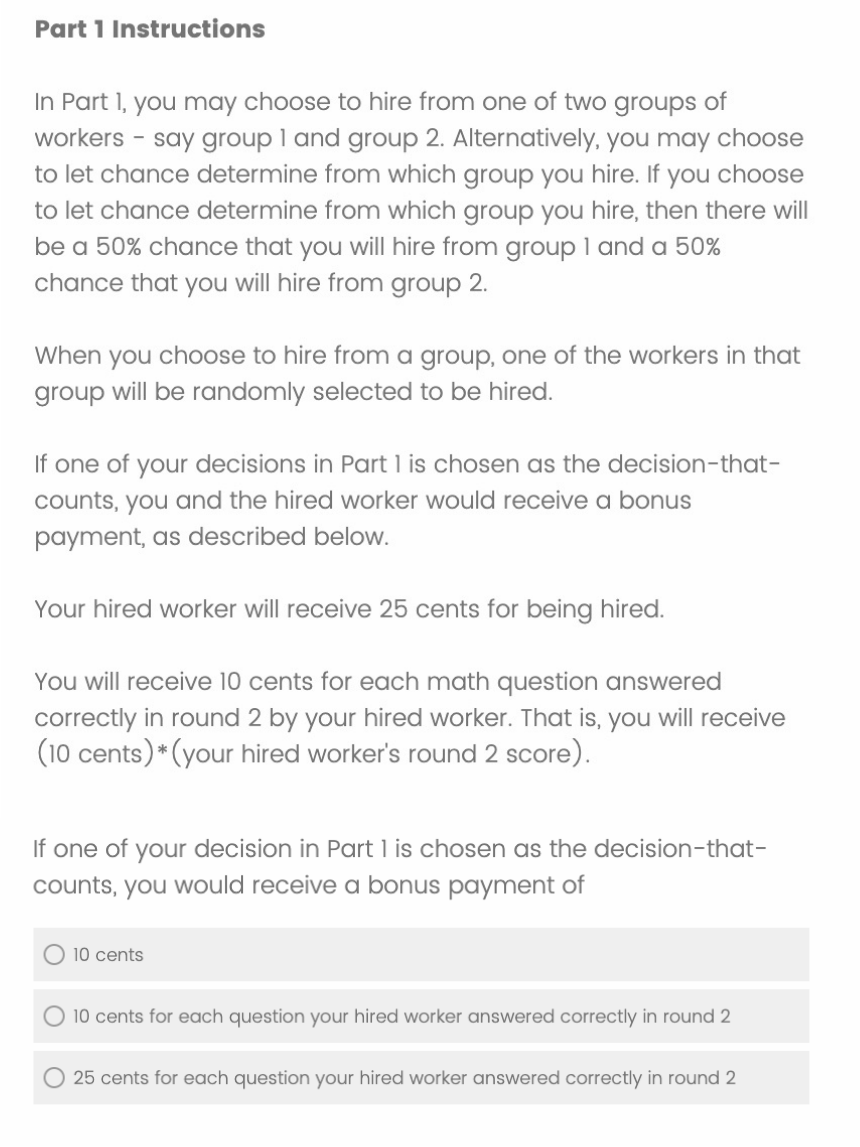


To help you make your hiring decisions, you will be provided with some information on the scores from which round?

○ Round 1

○ Round 2

The instructions and understanding question shown below ensure that participants understand the payoffs that result from taking their Part 1 decisions.



Part 1 Instructions

In Part 1, you may choose to hire from one of two groups of workers - say group 1 and group 2. Alternatively, you may choose to let chance determine from which group you hire. If you choose to let chance determine from which group you hire, then there will be a 50% chance that you will hire from group 1 and a 50% chance that you will hire from group 2.

When you choose to hire from a group, one of the workers in that group will be randomly selected to be hired.

If one of your decisions in Part 1 is chosen as the decision-that-counts, you and the hired worker would receive a bonus payment, as described below.

Your hired worker will receive 25 cents for being hired.

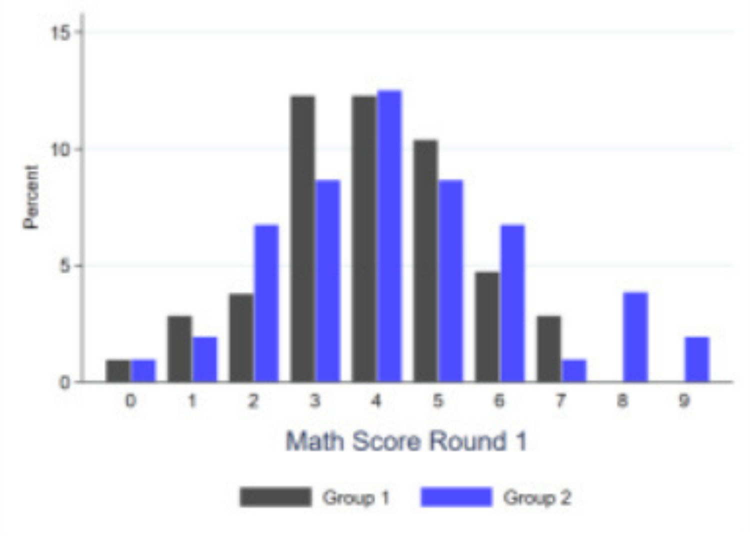
You will receive 10 cents for each math question answered correctly in round 2 by your hired worker. That is, you will receive (10 cents)*(your hired worker's round 2 score).

If one of your decision in Part 1 is chosen as the decision-that-counts, you would receive a bonus payment of

- ○ 10 cents
- ○ 10 cents for each question your hired worker answered correctly in round 2
- ○ 25 cents for each question your hired worker answered correctly in round 2

The fugure below and the understanding questions ensure that participants understand the content displayed in the form of a bar chart.

Additionally when deciding whether to hire from group 1 or group 2, or to let chance determine from which group you will hire from, you will be provided with information on the round 1 scores of the math questions for the workers in both group 1 and group 2 via a graph like the one below.



The bars in the graph represent the percent of workers in group 1 and group 2 who received a specific score in round 1 of the math questions. The axis labelled "Math Score in Round 1" lists the possible round 1 scores for workers and the axis labelled "Percent" lists the possible percentages. Group 1 is represented by the black bars and group 2 is represented by the blue bars.

Taller bars located more towards the right side of the graph indicate that a higher percentage of participants had high scores, while taller bars located more towards the left side of the graph indicate that a higher percentage of participants had low scores.

In the graph above, for example, the first pair of bars on the left hand side shows that approximately 1% of workers in both group 1 and group 2 had a score of 0. The third pair of bars on the left hand side of the graph shows that less than 5% of workers in group 1 had a score of 2 and more than 5% of workers in group 2 had a score of 2. The last bar on the right hand side of the graph shows that no worker in group 1 had a score of 9 and approximately 2% of workers in group 2 had a score of 9.

Taller bars located towards the left side of the graph indicate that

○ A smaller percentage of workers had a low score

○ A smaller percentage of workers had a high score

○ A larger percentage of workers had a low score

○ A larger percentage of workers had a high score

Taller bars located towards the right side of the graph indicate that

○ A smaller percentage of workers had a low score

○ A smaller percentage of workers had a high score

○ A larger percentage of workers had a low score

○ A larger percentage of workers had a high score

From the above graph, approximately what percent of workers in group 1 had a round 1 score of 6?

○ 10

○ 20

○ 30

○ 0

○ 5

From the above graph, approximately what percent of workers in group 2 had a round 1 score of 6?

○ 15

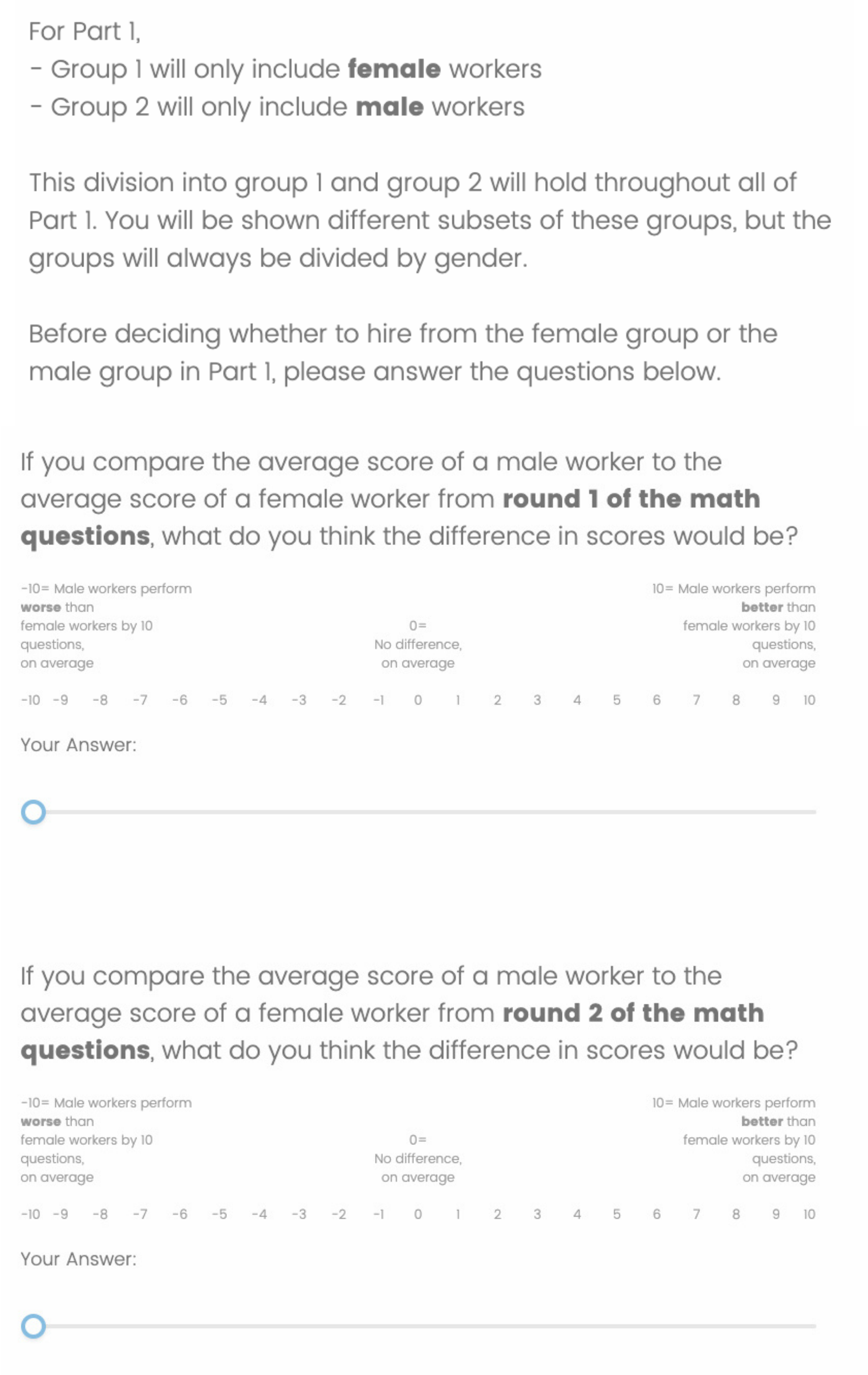
○ 2

○ 0

○ 10

○ 7

After completing all the previous understanding questions successfully, participants must answer a set of questions that measure their prior beliefs about the performance gap between male and female workers. Next, participants are asked to make 9 hiring decisions based on performance information of workers provided in the form of a bar chart comparing the distribution of female and male. All employers make the same 9 hiring decisions. However, the order of the first 8 distributions is randomized at the participant level. These 8 sets of distributions are formed by restricting the subset of workers to those born during different date ranges. For all participants, the 9th and final set of distributions contains the full distributions.



For Part 1,
- Group 1 will only include **female** workers
- Group 2 will only include **male** workers

This division into group 1 and group 2 will hold throughout all of Part 1. You will be shown different subsets of these groups, but the groups will always be divided by gender.

Before deciding whether to hire from the female group or the male group in Part 1, please answer the questions below.

If you compare the average score of a male worker to the average score of a female worker from **round 1 of the math questions**, what do you think the difference in scores would be?

-10= Male workers perform **worse** than female workers by 10 questions, on average

0= No difference, on average

10= Male workers perform **better** than female workers by 10 questions, on average

Your Answer:

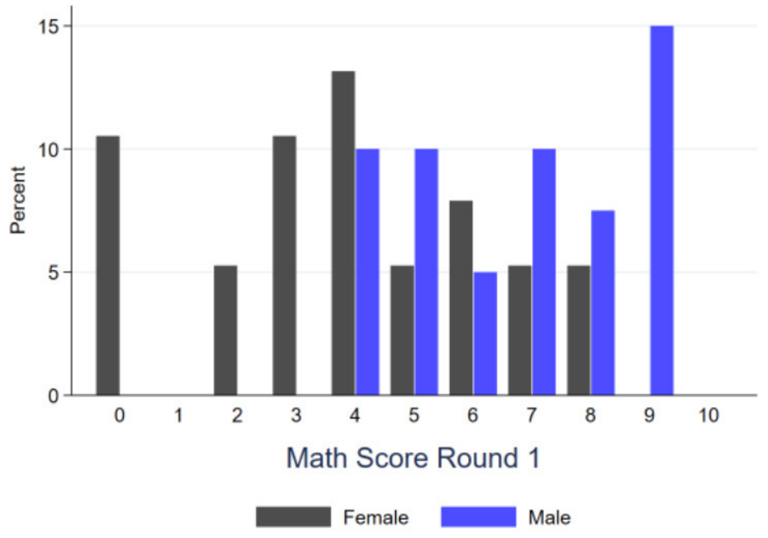
If you compare the average score of a male worker to the average score of a female worker from **round 2 of the math questions**, what do you think the difference in scores would be?

-10= Male workers perform **worse** than female workers by 10 questions, on average

0= No difference, on average

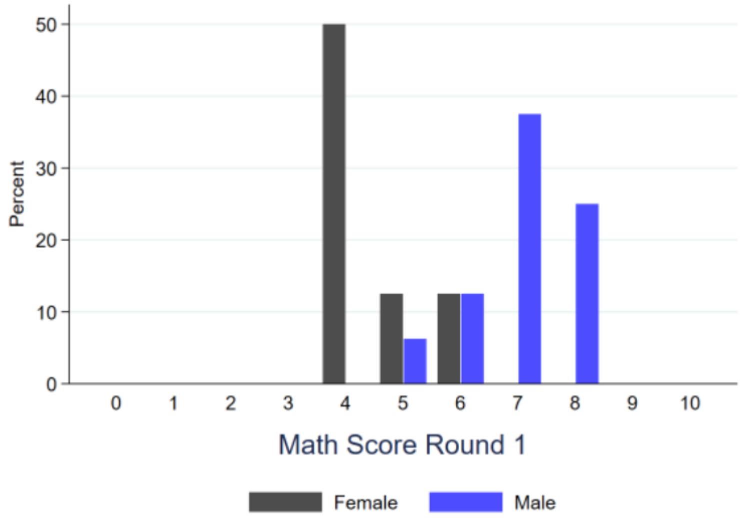
10= Male workers perform **better** than female workers by 10 questions, on average

Your Answer:



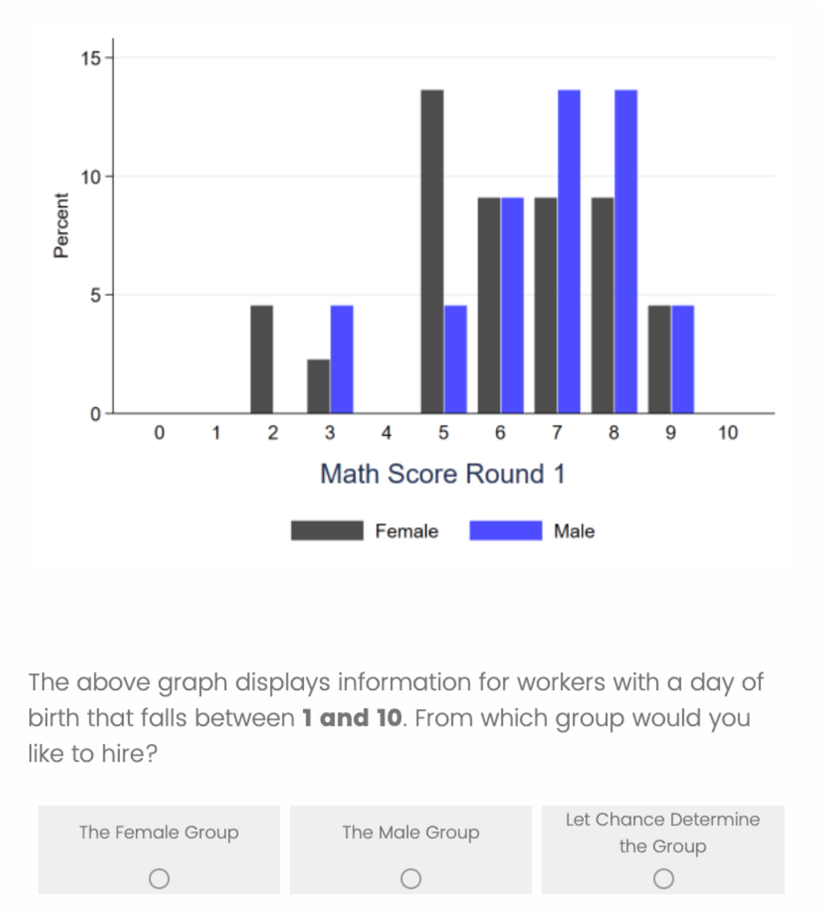
The above graph displays information for workers with a day of birth that falls between **21 and 31**. From which group would you like to hire?

The Female Group ○	The Male Group ○	Let Chance Determine the Group ○



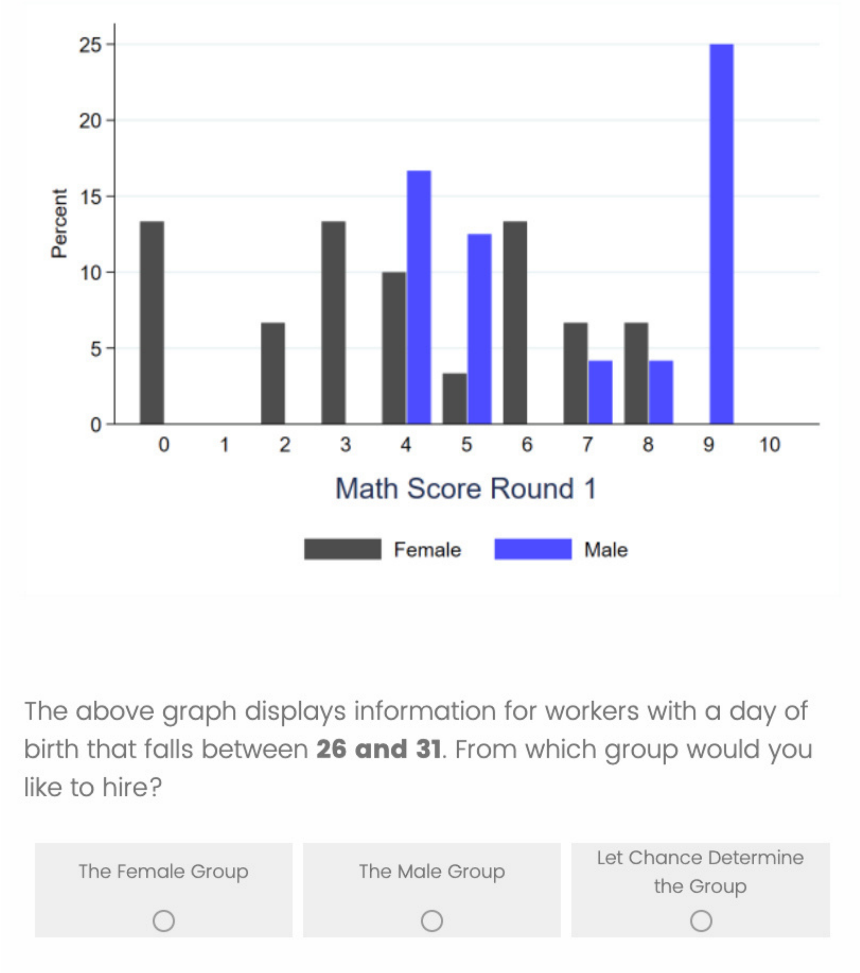
The above graph displays information for workers with a day of birth that falls between **21 and 25**. From which group would you like to hire?

The Female Group ○	The Male Group ○	Let Chance Determine the Group ○



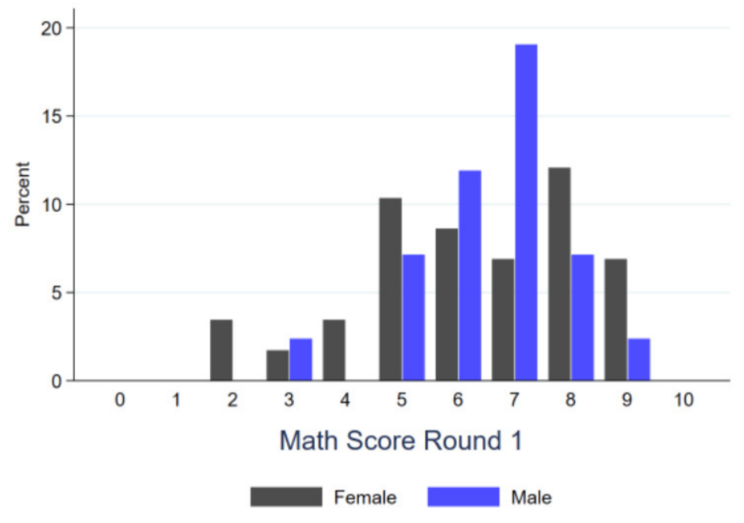
The above graph displays information for workers with a day of birth that falls between **1 and 10**. From which group would you like to hire?

The Female Group ○	The Male Group ○	Let Chance Determine the Group ○



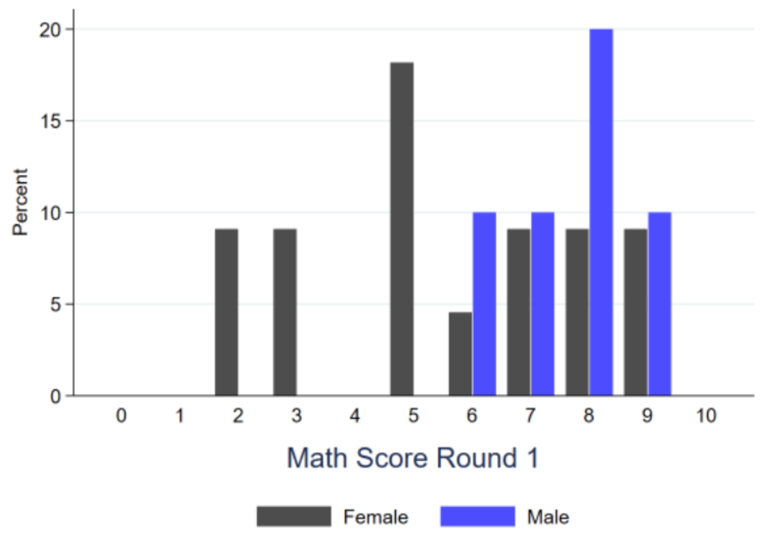
The above graph displays information for workers with a day of birth that falls between **26 and 31**. From which group would you like to hire?

The Female Group ○	The Male Group ○	Let Chance Determine the Group ○



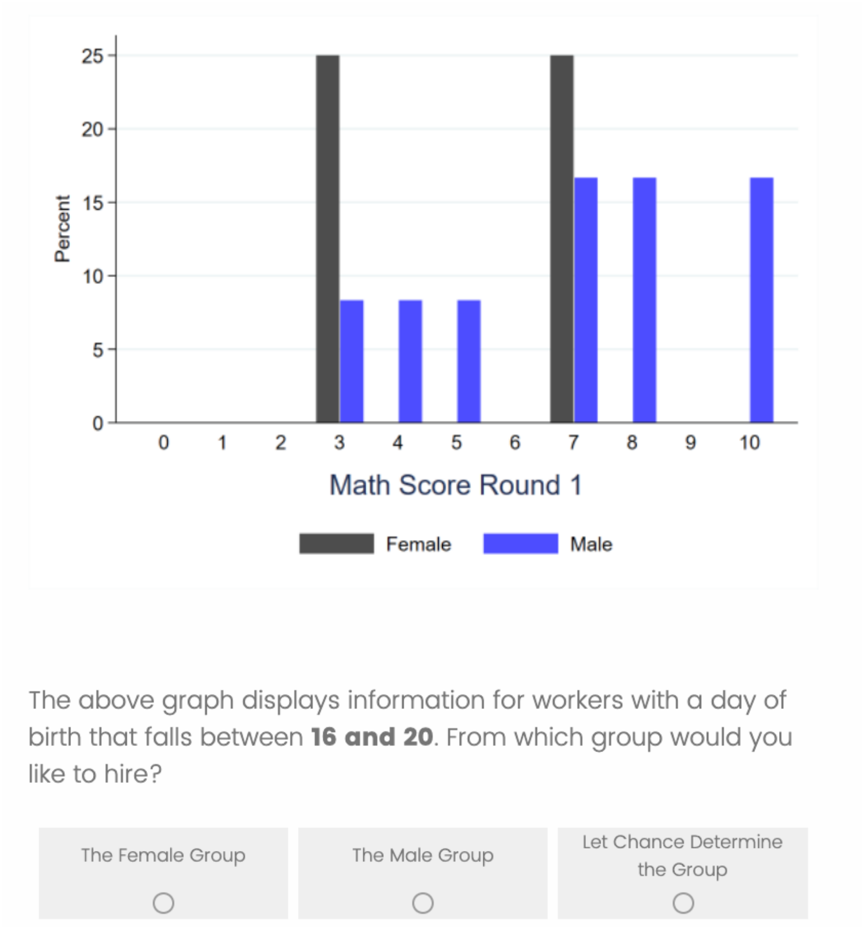
The above graph displays information for workers with a day of birth that falls between **1 and 15**. From which group would you like to hire?

The Female Group ○	The Male Group ○	Let Chance Determine the Group ○



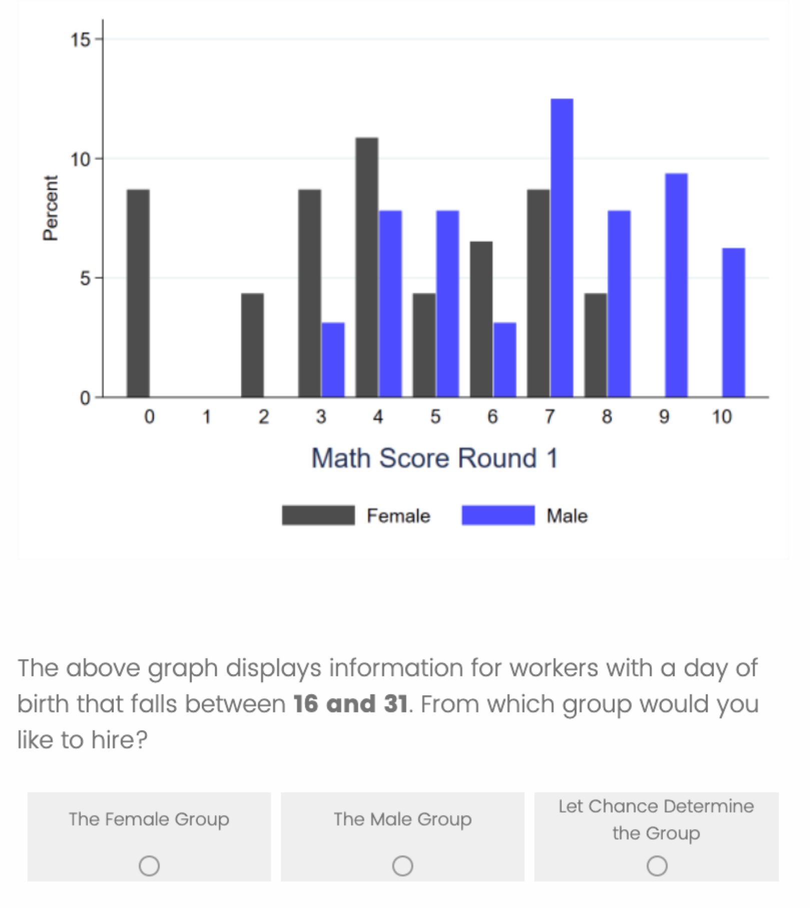
The above graph displays information for workers with a day of birth that falls between **6 and 10**. From which group would you like to hire?

The Female Group ○	The Male Group ○	Let Chance Determine the Group ○



The above graph displays information for workers with a day of birth that falls between **16 and 20**. From which group would you like to hire?

The Female Group	The Male Group	Let Chance Determine the Group
○	○	○

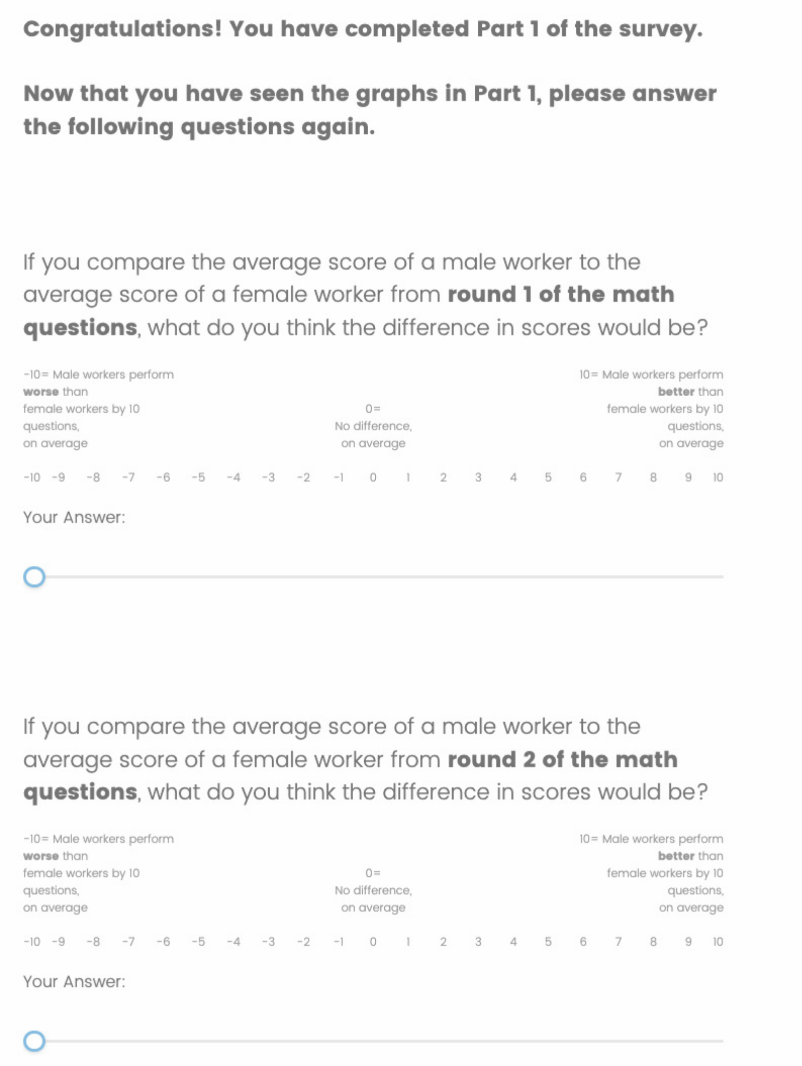


The above graph displays information for workers with a day of birth that falls between **16 and 31**. From which group would you like to hire?

The Female Group	The Male Group	Let Chance Determine the Group
○	○	○

The above graph displays information for workers **across all** days of birth. From which group would you like to hire?

After the participants have made their 9 decisions, we elicit their posterior beliefs of average differences in performance across the two groups. These questions are identical to the prior belief measurement questions.



Congratulations! You have completed Part 1 of the survey.

Now that you have seen the graphs in Part 1, please answer the following questions again.

If you compare the average score of a male worker to the average score of a female worker from **round 1 of the math questions**, what do you think the difference in scores would be?

-10= Male workers perform **worse** than female workers by 10 questions, on average

0= No difference, on average

10= Male workers perform **better** than female workers by 10 questions, on average

Your Answer:

If you compare the average score of a male worker to the average score of a female worker from **round 2 of the math questions**, what do you think the difference in scores would be?

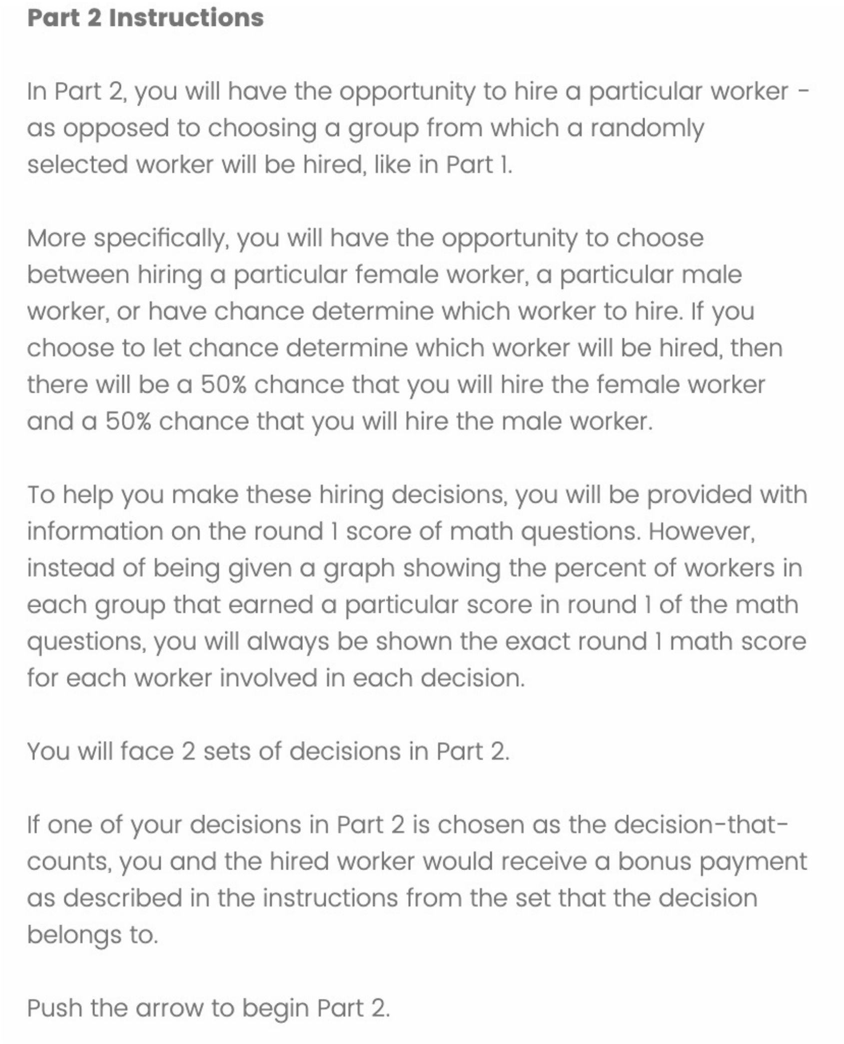
-10= Male workers perform **worse** than female workers by 10 questions, on average

0= No difference, on average

10= Male workers perform **better** than female workers by 10 questions, on average

Your Answer:

In Part 2 the participant is asked to make 2 sets of decisions. Each set of decisions contains 9 hiring decisions. The hiring decisions in the two sets are identical and only the payoff for the employer changes. The information on the payoff structure is shown on a separate screen and contains understanding questions.



Part 2 Instructions

In Part 2, you will have the opportunity to hire a particular worker - as opposed to choosing a group from which a randomly selected worker will be hired, like in Part 1.

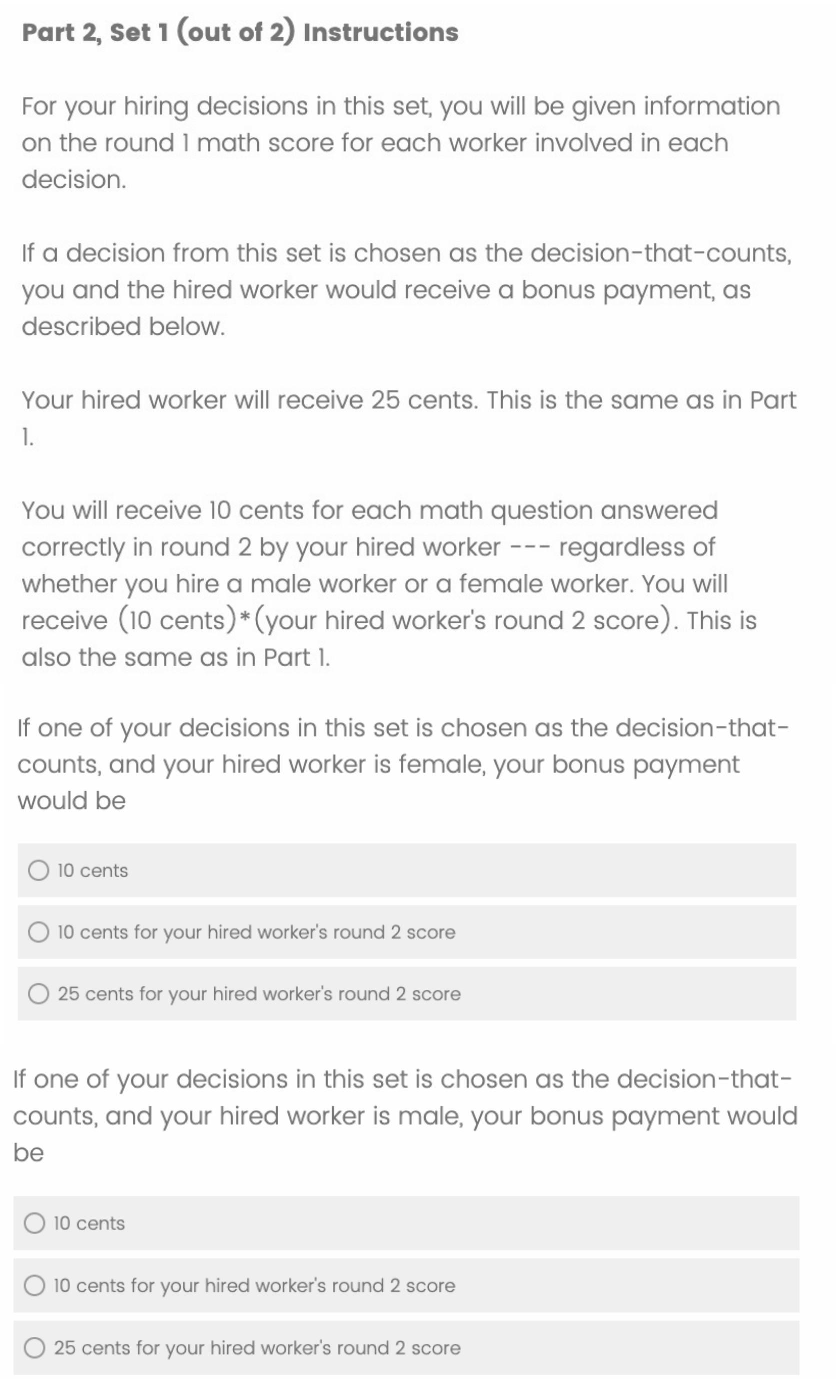
More specifically, you will have the opportunity to choose between hiring a particular female worker, a particular male worker, or have chance determine which worker to hire. If you choose to let chance determine which worker will be hired, then there will be a 50% chance that you will hire the female worker and a 50% chance that you will hire the male worker.

To help you make these hiring decisions, you will be provided with information on the round 1 score of math questions. However, instead of being given a graph showing the percent of workers in each group that earned a particular score in round 1 of the math questions, you will always be shown the exact round 1 math score for each worker involved in each decision.

You will face 2 sets of decisions in Part 2.

If one of your decisions in Part 2 is chosen as the decision-that-counts, you and the hired worker would receive a bonus payment as described in the instructions from the set that the decision belongs to.

Push the arrow to begin Part 2.



Part 2, Set 1 (out of 2) Instructions

For your hiring decisions in this set, you will be given information on the round 1 math score for each worker involved in each decision.

If a decision from this set is chosen as the decision-that-counts, you and the hired worker would receive a bonus payment, as described below.

Your hired worker will receive 25 cents. This is the same as in Part 1.

You will receive 10 cents for each math question answered correctly in round 2 by your hired worker --- regardless of whether you hire a male worker or a female worker. You will receive (10 cents)*(your hired worker's round 2 score). This is also the same as in Part 1.

If one of your decisions in this set is chosen as the decision-that-counts, and your hired worker is female, your bonus payment would be

○ 10 cents

○ 10 cents for your hired worker's round 2 score

○ 25 cents for your hired worker's round 2 score

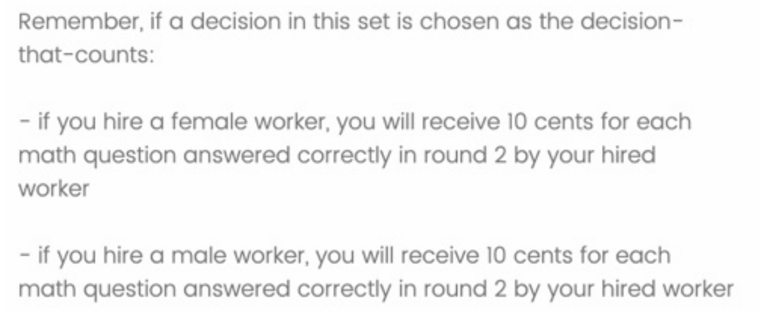
If one of your decisions in this set is chosen as the decision-that-counts, and your hired worker is male, your bonus payment would be

○ 10 cents

○ 10 cents for your hired worker's round 2 score

○ 25 cents for your hired worker's round 2 score

After having answered all the understanding questions correctly, the participant sees the 9 hiring decisions-to-be-made on one page.



Remember, if a decision in this set is chosen as the decision-that-counts:

- if you hire a female worker, you will receive 10 cents for each math question answered correctly in round 2 by your hired worker

- if you hire a male worker, you will receive 10 cents for each math question answered correctly in round 2 by your hired worker

Hiring Decision 1:

Female worker (round 1 score= 4) ○	Male worker (round 1 score= 4) ○	Let chance determine who is hired ○

Hiring Decision 2:

Female worker (round 1 score= 5) ○	Male worker (round 1 score= 4) ○	Let chance determine who is hired ○

Hiring Decision 3:

Female worker (round 1 score= 6) ○	Male worker (round 1 score= 4) ○	Let chance determine who is hired ○

Hiring Decision 4:

Female worker (round 1 score= 7) ○	Male worker (round 1 score= 4) ○	Let chance determine who is hired ○

Hiring Decision 5:

Female worker (round 1 score= 8) ○	Male worker (round 1 score= 4) ○	Let chance determine who is hired ○

Hiring Decision 6:

Female worker (round 1 score= 6) ○	Male worker (round 1 score= 6) ○	Let chance determine who is hired ○

Hiring Decision 7:

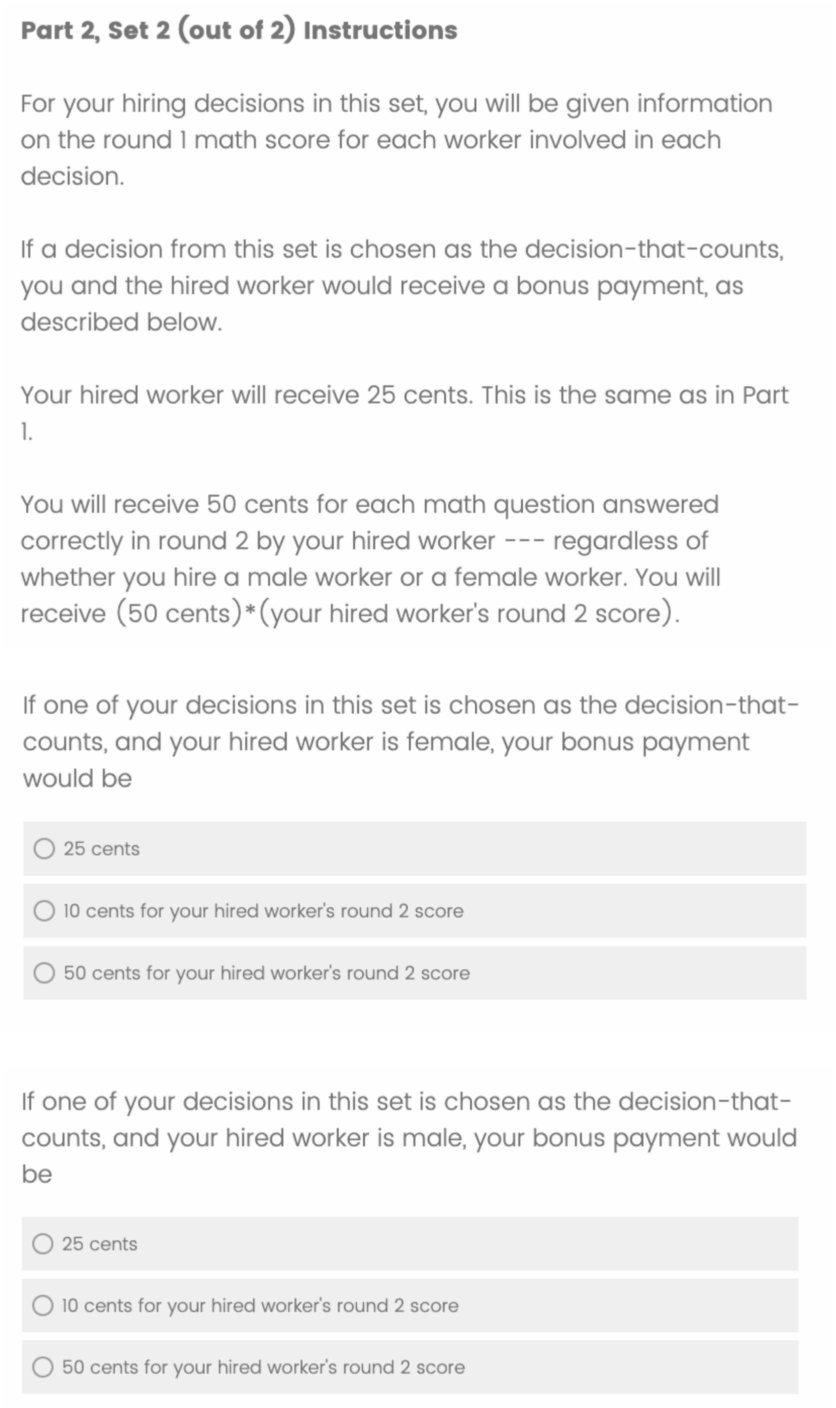
Female worker (round 1 score= 7) ○	Male worker (round 1 score= 6) ○	Let chance determine who is hired ○

Hiring Decision 8:

Female worker (round 1 score= 8) ○	Male worker (round 1 score= 6) ○	Let chance determine who is hired ○

Hiring Decision 9:

Female worker (round 1 score= 8) ○	Male worker (round 1 score= 8) ○	Let chance determine who is hired ○



Part 2, Set 2 (out of 2) Instructions

For your hiring decisions in this set, you will be given information on the round 1 math score for each worker involved in each decision.

If a decision from this set is chosen as the decision-that-counts, you and the hired worker would receive a bonus payment, as described below.

Your hired worker will receive 25 cents. This is the same as in Part 1.

You will receive 50 cents for each math question answered correctly in round 2 by your hired worker --- regardless of whether you hire a male worker or a female worker. You will receive (50 cents)*(your hired worker's round 2 score).

If one of your decisions in this set is chosen as the decision-that-counts, and your hired worker is female, your bonus payment would be

○ 25 cents

○ 10 cents for your hired worker's round 2 score

○ 50 cents for your hired worker's round 2 score

If one of your decisions in this set is chosen as the decision-that-counts, and your hired worker is male, your bonus payment would be

○ 25 cents

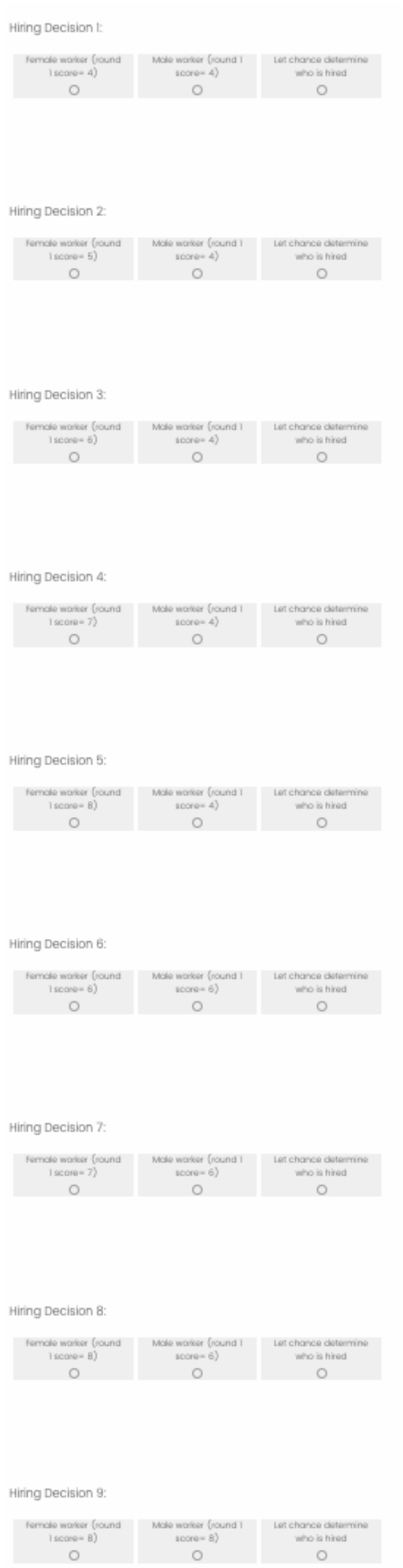
○ 10 cents for your hired worker's round 2 score

○ 50 cents for your hired worker's round 2 score

Remember, if a decision in this set is chosen as the decision-that-counts:

- if you hire a female worker, you will receive 50 cents for each math question answered correctly in round 2 by your hired worker

- if you hire a male worker, you will receive 50 cents for each math question answered correctly in round 2 by your hired worker



Hiring Decision 1:

Female worker (round 1 score= 4) ○	Male worker (round 1 score= 4) ○	Let chance determine who is hired ○

Hiring Decision 2:

Female worker (round 1 score= 5) ○	Male worker (round 1 score= 4) ○	Let chance determine who is hired ○

Hiring Decision 3:

Female worker (round 1 score= 6) ○	Male worker (round 1 score= 4) ○	Let chance determine who is hired ○

Hiring Decision 4:

Female worker (round 1 score= 7) ○	Male worker (round 1 score= 4) ○	Let chance determine who is hired ○

Hiring Decision 5:

Female worker (round 1 score= 8) ○	Male worker (round 1 score= 4) ○	Let chance determine who is hired ○

Hiring Decision 6:

Female worker (round 1 score= 6) ○	Male worker (round 1 score= 6) ○	Let chance determine who is hired ○

Hiring Decision 7:

Female worker (round 1 score= 7) ○	Male worker (round 1 score= 6) ○	Let chance determine who is hired ○

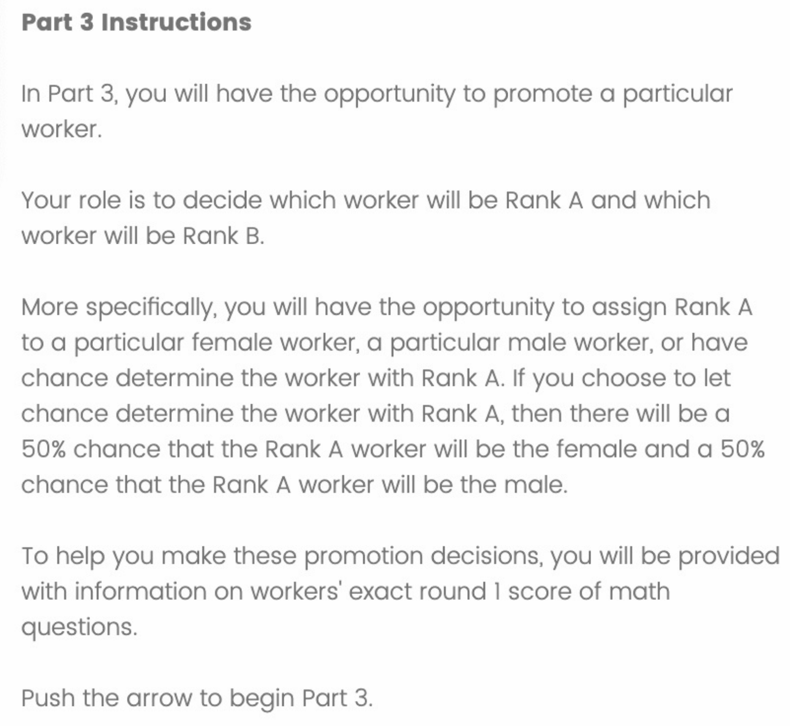
Hiring Decision 8:

Female worker (round 1 score= 8) ○	Male worker (round 1 score= 6) ○	Let chance determine who is hired ○

Hiring Decision 9:

Female worker (round 1 score= 8) ○	Male worker (round 1 score= 8) ○	Let chance determine who is hired ○

In Part 3 the participant is asked to make a last set of decisions. This last set of decisions contains 9 promotion decisions. The information on the payoff structure is shown on a separate screen and contains understanding questions. After completing Part 2, participants answer a follow-up demographic questionnaire. We distributed the relevant payments after the study was completed.



Part 3 Instructions

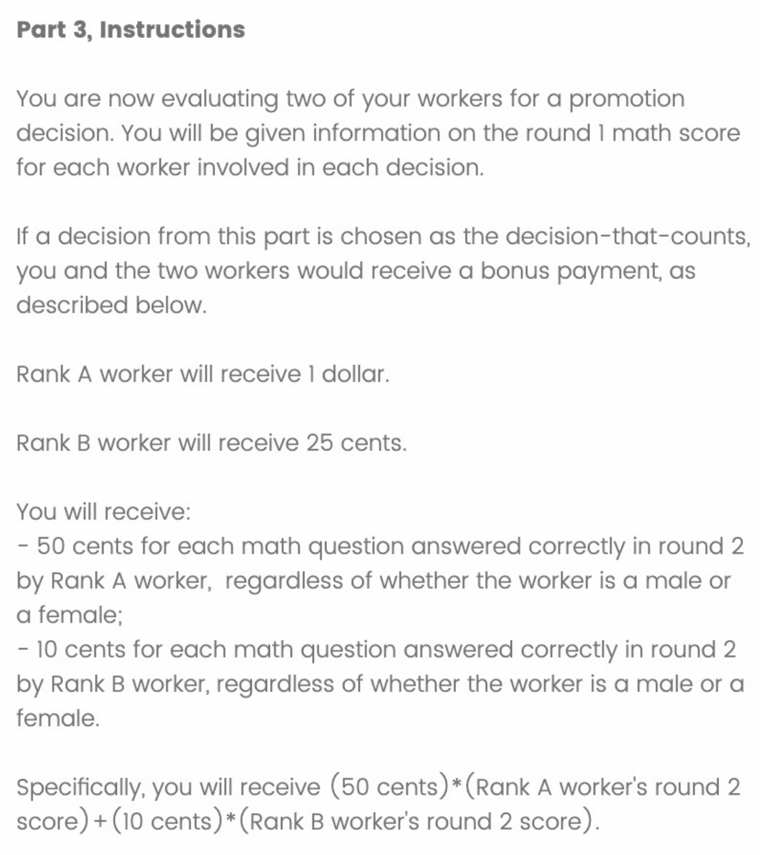
In Part 3, you will have the opportunity to promote a particular worker.

Your role is to decide which worker will be Rank A and which worker will be Rank B.

More specifically, you will have the opportunity to assign Rank A to a particular female worker, a particular male worker, or have chance determine the worker with Rank A. If you choose to let chance determine the worker with Rank A, then there will be a 50% chance that the Rank A worker will be the female and a 50% chance that the Rank A worker will be the male.

To help you make these promotion decisions, you will be provided with information on workers' exact round 1 score of math questions.

Push the arrow to begin Part 3.



Part 3, Instructions

You are now evaluating two of your workers for a promotion decision. You will be given information on the round 1 math score for each worker involved in each decision.

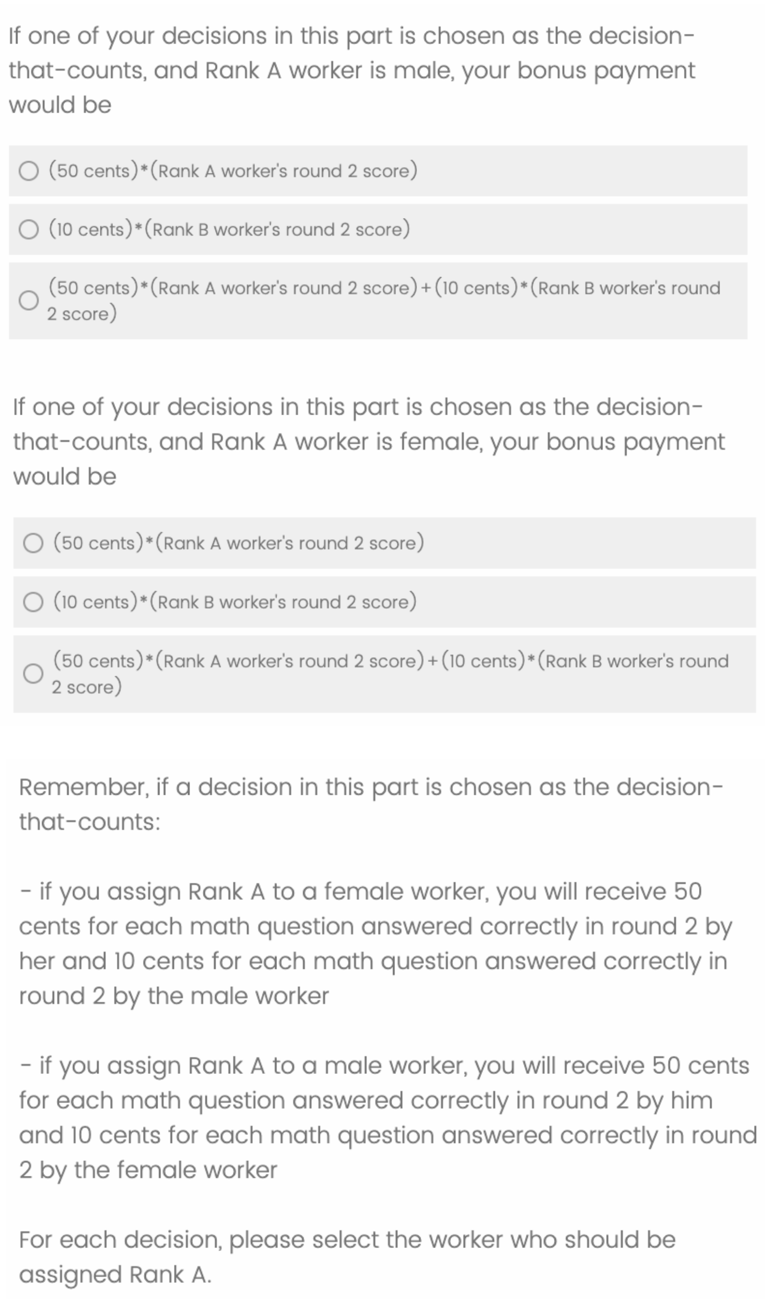
If a decision from this part is chosen as the decision-that-counts, you and the two workers would receive a bonus payment, as described below.

Rank A worker will receive 1 dollar.

Rank B worker will receive 25 cents.

You will receive:
- 50 cents for each math question answered correctly in round 2 by Rank A worker, regardless of whether the worker is a male or a female;
- 10 cents for each math question answered correctly in round 2 by Rank B worker, regardless of whether the worker is a male or a female.

Specifically, you will receive (50 cents)*(Rank A worker's round 2 score)+(10 cents)*(Rank B worker's round 2 score).



If one of your decisions in this part is chosen as the decision-that-counts, and Rank A worker is male, your bonus payment would be

○ (50 cents)*(Rank A worker's round 2 score)

○ (10 cents)*(Rank B worker's round 2 score)

○ (50 cents)*(Rank A worker's round 2 score) + (10 cents)*(Rank B worker's round 2 score)

If one of your decisions in this part is chosen as the decision-that-counts, and Rank A worker is female, your bonus payment would be

○ (50 cents)*(Rank A worker's round 2 score)

○ (10 cents)*(Rank B worker's round 2 score)

○ (50 cents)*(Rank A worker's round 2 score) + (10 cents)*(Rank B worker's round 2 score)

Remember, if a decision in this part is chosen as the decision-that-counts:

- if you assign Rank A to a female worker, you will receive 50 cents for each math question answered correctly in round 2 by her and 10 cents for each math question answered correctly in round 2 by the male worker

- if you assign Rank A to a male worker, you will receive 50 cents for each math question answered correctly in round 2 by him and 10 cents for each math question answered correctly in round 2 by the female worker

For each decision, please select the worker who should be assigned Rank A.

Promotion Decision 1:

Female worker (round 1 score= 4) ○	Male worker (round 1 score= 4) ○	Let chance determine who is promoted ○

Promotion Decision 2:

Female worker (round 1 score= 5) ○	Male worker (round 1 score= 4) ○	Let chance determine who is promoted ○

Promotion Decision 3:

Female worker (round 1 score= 6) ○	Male worker (round 1 score= 4) ○	Let chance determine who is promoted ○

Promotion Decision 4:

Female worker (round 1 score= 7) ○	Male worker (round 1 score= 4) ○	Let chance determine who is promoted ○

Promotion Decision 5:

Female worker (round 1 score= 8) ○	Male worker (round 1 score= 4) ○	Let chance determine who is promoted ○

Promotion Decision 6:

Female worker (round 1 score= 6) ○	Male worker (round 1 score= 6) ○	Let chance determine who is promoted ○

Promotion Decision 7:

Female worker (round 1 score= 7) ○	Male worker (round 1 score= 6) ○	Let chance determine who is promoted ○

Promotion Decision 8:

Female worker (round 1 score= 8) ○	Male worker (round 1 score= 6) ○	Let chance determine who is promoted ○

Promotion Decision 9:

Female worker (round 1 score= 8) ○	Male worker (round 1 score= 8) ○	Let chance determine who is promoted ○