

# Gender Differences in the Cost of Corrections in Group Work

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## Abstract

Collaboration is integral in most workplaces, which also involves correcting one's colleagues. Using a quasi-laboratory experiment, I study whether people dislike collaborating with someone who corrects them and whether the dislike is stronger when that person is a woman. I find that people, including those with high productivity, are less willing to collaborate with someone who has corrected them even if the correction improved group performance. In addition, I find suggestive evidence that men respond more negatively to women's corrections and that men's beliefs about gender differences in abilities cannot explain this differential response. These findings suggest a behavioral bias distorts the optimal selection of talents and penalizes those who correct others' mistakes, and the distortion may be stronger when women correct men.

**JEL codes:** J16, M54, D91, C92

**Keywords:** correction, collaboration, group work, gender differences, quasi-laboratory experiment

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# 1 Introduction

Collaboration is at the core of most workplaces as they involve group work (Jones 2021; Lazear and Shaw 2007; Wuchty, Jones, and Uzzi 2007). However, on occasion, it also involves correcting one’s colleagues: hiring committee members can have different opinions about the best candidates among the applicants, and co-authors in a research project can have conflicting views about the best experimental design or identification strategy. Since people avoid information that conflicts with their own beliefs (Abelson 1986; Golman, Hagmann, and Loewenstein 2017),<sup>1</sup> corrections may damage the collaborative relationship. This potential interpersonal friction can be detrimental to group efficiency because workplace climate is an important determinant of productivity (Alan, Corekcioglu, and Sutter 2021; Edmans 2011; Guiso, Sapienza, and Zingales 2015). In addition, women may experience stronger interpersonal friction because people often become more hostile toward women (Dupas et al. 2021), which can contribute to the gender gap in labor market outcomes (Blau and Kahn 2017).

This paper studies whether people dislike collaborating with someone who corrects them and whether the dislike is stronger when that person is a woman. Answering this question using secondary data poses two challenges. First, group formation is not random, and group corrections are endogenous. Second, different corrections are not necessarily comparable to each other.

To overcome these challenges, I design a quasi-laboratory experiment, a hybrid of physical laboratory and online experiments, where group formation is randomized and define corrections such that researchers can track its quality mathematically. Specifically, participants are allocated to a group of eight and solve one collaborative task with each group member one by one. Each time participants finish the task, they state whether they would like to collaborate with the group member with whom they have just solved the task for the same task in the next stage, which is the main source of earnings. This gives a strong incentive for participants to select as good a collaborator as possible. The order of the group members with whom participants solve the task is randomized. As a collaborative task, I use Isaksson (2018)’s number-sliding puzzle, which allows me to calculate an objective measure of each participant’s contribution to the collaborative task and to classify each move as good (move the puzzle closer to the solution) or bad (move the puzzle further away from the solution). I define a correction as reversing a group member’s move, comparable across different participants, and can be classified as either good or bad.

I find that people correctly understand the notion of good and bad moves; the higher one’s contribution to solving the puzzle, the more likely it is that they are asked to be a collaborator. This is in line with what one would expect and validates my experimental design. Nonetheless, after controlling for the contribution, people are less willing to collaborate with someone who has corrected their moves, even if the corrections move the puzzle closer to the solution. This is not because people misunderstood good corrections as bad ones, because high productivity people – who should be able to better identify good and bad corrections – also respond negatively to corrections.

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1. Information avoidance is sometimes rational; see Golman, Hagmann, and Loewenstein (2017).

Thus, the negative response is likely to be irrational. Although only suggestive, I also find evidence that men respond more negatively to women’s good corrections: men may dislike women correcting their mistakes. This finding is unlikely to be due to men’s beliefs about the differences in women’s and men’s abilities in the puzzle: women and men contribute equally well to the puzzle, and neither women nor men underestimate women’s contribution.

Taken together, these findings suggest a behavioral bias distorts the optimal selection of talents and penalizes those who correct others’ mistakes, and men may exhibit stronger bias when women correct them.

This paper’s contribution is twofold. First, it contributes to the literature on the workplace climate and productivity by showing that interpersonal frictions can distort group efficiency, and friction may have a stronger effect on women. My findings complement Alan, Corekcioglu, and Sutter (2021), who find that a better workplace climate increases worker satisfaction and the degree of mutual reciprocation while reducing toxic competition and worker turnover and argue that improved manager-worker relationships are the likely mechanism. Aside from Alan et al., my findings also relate to the organizational economics literature. It finds that firms with high employee satisfaction exhibit higher stock prices (Edmans 2011) and that a firm performs better when its workers perceive their managers as trustworthy and ethical (Guiso, Sapienza, and Zingales 2015). Further, I show that the same environment can affect women differently, which corroborates Dupas et al. (2021), who find female economists receive more patronizing and hostile questions during seminars, and Folke and Rickne (2022), who find that women in male-dominant jobs receive more harassment.<sup>2</sup>

Second, this paper contributes to the literature on differential treatment of women’s opinions by showing that women’s corrections may receive stronger negative reactions. My findings primarily complement Guo and Recalde (2022), who find that group members correct women’s ideas more often than men’s, and Coffman, Flikkema, and Shurchkov (2021), who find that group members are less likely to choose women’s answers as a group answer in male-typed questions.

The remainder of the paper proceeds as follows. Section 2 describes the experimental design, procedure, and implementation. Section 3 describes the data. Section 4 presents a simple theoretical framework. Section ?? presents evidence that people are less willing to collaborate with a person who has corrected their moves, even if the corrections move the puzzle closer to the solution and that even high productivity people respond negatively to corrections. Section ?? presents suggestive evidence that men respond more negatively to women’s good corrections. Section 7 presents the robustness of the results. Section 8 concludes.

## 2 Experiment

**Introducing a quasi-laboratory format** I run the experiment in a quasi-laboratory format where we experimenters connect us to the participants via Zoom throughout the experiment (but turn off participants’ camera and microphone except at the beginning of the experiment) and

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2. Folke and Rickne (2022) also find the opposite: men in female-dominant jobs receive more harassment.

conduct it as we usually do in a physical laboratory, but participants participate remotely using their computers. Appendix A discusses the advantages and drawbacks of the quasi-laboratory format relative to physical laboratory and standard online experiments.

Figure 1: Puzzle screen

## Puzzle 4 out of 7

Time left to complete this page: 1:53

You are playing the puzzle with **Valeria**

1	2	3
8	7	5
	4	6

It's your turn!

*Notes:* This shows a sample puzzle screen where a participant is matched with another participant called Valeria at the 4th round of the puzzle and making their move. All the texts are in Italian in the experiment.

**Collaborative task** As the collaborative task, I use Isaksson (2018)'s puzzle, a sliding puzzle with eight numbered tiles, which should be placed in numerical order within a 3x3 frame (see Figure 1 for an example). To achieve this goal, participants play in pairs, alternating their moves.<sup>3</sup> This puzzle has nice mathematical properties: I can define the puzzle difficulty and classify a given move as either good or bad by the Breadth-First Search algorithm.<sup>4</sup> From the number of good and bad moves one makes, I can calculate individual contributions to the task; I measure it by net good moves, the number of good moves minus the number of bad moves an individual makes in a given puzzle.

I can also determine the quality of corrections of different participants objectively and comparably.<sup>5</sup> Further, puzzle-solving captures an essential characteristic of collaborative work in which two or more people work towards the same goal (Isaksson 2018), but the quality of each move and correction is only partially observable to participants (but fully observable to the experimenter).

3. Each participant has to make a move in their turn; they cannot pass.

4. The difficulty is defined as the number of moves away from the solution, a good move is defined as a move that reduces the number of moves away from the solution, and a bad move is defined as a move that increases the number of moves away from the solution.

5. Indeed, some corrections happen early in the puzzle and the other later in the puzzle. Thus, what I capture in the analysis is the average effect of a correction.

At each stage of the puzzle, there is only one good strategy which is to make a good move, and one bad strategy which is to make a bad move.<sup>6</sup> There can be more than one good and bad move, but different good/bad moves are equal. There is no path dependence either: the history of the puzzle moves does not matter.

At the beginning of each part, participants must answer a set of comprehension questions to ensure they understand the instructions.<sup>7</sup>

## 2.1 Design and procedure

### Registration

Upon receiving an invitation email to the experiment, participants register for a session they want to participate in, upload their ID documents, and a signed consent form.<sup>8</sup>

### Pre-experiment

Participants enter the Zoom waiting room on the day and the time of the session they have registered for.<sup>9</sup> They receive a link to the virtual room for the experiment and enter their first name, last name, and their email address they have used in the registration. They also draw a virtual coin numbered from 1 to 40 without replacement.

Then I admit participants to the Zoom meeting room one by one and rename them by the first name they have just entered. This information is necessary to match up their earnings in this experiment and their payment information stored in the laboratory database, so participants have a strong incentive to provide their true name and email address. If there is more than one participant with the same first name, I add a number after their first name (e.g., Giovanni2).

After admitting all the participants to the Zoom meeting room, I do roll call, a way to reveal participants' gender to other participants without making gender salient (Bordalo et al. 2019; Coffman, Flikkema, and Shurchkov 2021). Specifically, I take attendance by calling each participant's first name one by one and asking them to respond via microphone. This process ensures other participants that the called participant's first name corresponds to their gender. If there are more participants than I would need for the session (I need 16 participants), I draw random numbers from 1 to 40 and ask those who drew the coins with the same number to leave.<sup>10</sup> Those who leave the session receive the 2€ show-up fee. Figure 2 shows a Zoom screen participants would see during

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6. This is conditional on that both players are trying to solve the puzzle; I show in section 7 that the results are robust to exclusion of puzzles where either player might not be trying to solve the puzzle.

7. I do not tell participants that they can correct others to reduce experimenter demand effects.

8. I recruit a few more participants than I would need for a given session in case some participants would not show up to the session.

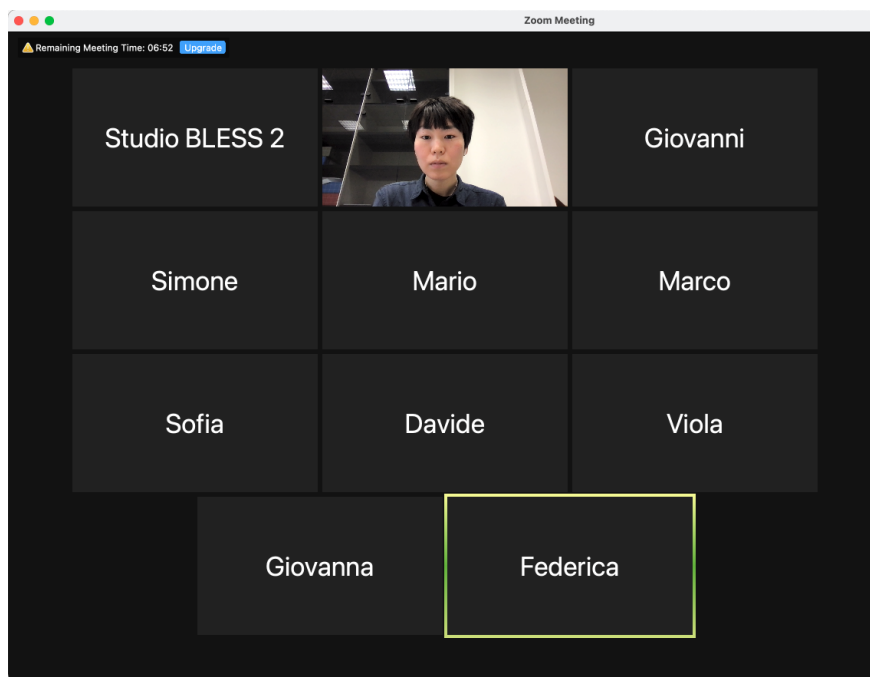
9. Zoom link is sent with an invitation email; I check that they have indeed registered for a given session before admitting them to the Zoom meeting room.

10. I draw with replacement a number from 1 to 40 using Google's random number generator (<https://www.google.com/search?q=random+number>). If no participant has a coin with the drawn number, I draw next number until the number of participants is 16. I share my computer screen so that participants see the numbers are actually drawn randomly.

the roll call (the person whose camera is on is the experimenter; participants would see this screen throughout the experiment, but the experimenter’s camera may be turned off).

I then read out the instructions about the rules of the experiment and take questions on Zoom. Once participants start the main part, they can communicate with the experimenter only via Zoom’s private chat.

Figure 2: Zoom screen



*Notes:* This figure shows a Zoom screen participants would see during the roll call. The experimenter’s camera is on during the roll call. Participants would see this screen throughout the experiment, but the experimenter’s camera may be turned off.

### Part 1: Individual practice stage

Participants work on the puzzle individually with an incentive (0.2€ for each puzzle they solve). They can solve as many puzzles as possible with increasing difficulty (maximum 15 puzzles) in 4 minutes. After the 4 minutes, they receive information on how many puzzles they have solved. This part familiarizes them with the puzzle and gives us a measure of their ability given by the number of puzzles they solve.

### Part 2: Collaborator selection stage

Part 2 contains seven rounds, and participants learn the rules of part 3 before starting part 2. This part is based on Fisman et al. (2006, 2008)’s speed dating experiments and proceeds as follows: first, participants are allocated to a group of 8 based on their ability similarity as measured in part 1. This is to reduce ability differences among participants, and participants are not told about this grouping criterion.

Second, participants are paired with another randomly chosen participant in the same group and solve one puzzle together by alternating their moves. The participant who makes the first move is drawn at random, and both participants know this first-mover selection criterion. If they cannot solve the puzzle within 2 minutes, they finish the puzzle without solving it. Participants are allowed to reverse the paired participant’s move.<sup>11</sup> Reversing the partner’s move is what I call correction in this paper. Each participant’s contribution to a given puzzle is measured by net good moves. Figure 1 shows a sample puzzle screen where a participant is paired with another participant called Valeria and making their move.<sup>12</sup> The paired participant’s first name is displayed on the computer screen throughout the puzzle, and when participants select their collaborator to subtly inform the paired participant’s gender.

Once they finish the puzzle, participants state whether they would like to collaborate with the same participant in part 3 (yes/no). At the end of the first round, new pairs are formed, with a perfect stranger matching procedure, so that every participant is paired with each of the other seven members of their group once and only once. In each round, participants solve another puzzle in a pair, then state whether they would like to collaborate with the same participant in part 3. The sequence of puzzles is the same for all pairs in all sessions. The puzzle difficulty is kept the same across the seven rounds. The minimum number of moves to solve the puzzles is set to 8 based on the pilot.

At the end of part 3, participants are paired according to the following algorithm:

1. For every participant, call it  $i$ , I count the number of matches; that is, the number of other participants in the group who were willing to be paired with  $i$  and with whom  $i$  is willing to collaborate in part 3.
2. I randomly choose one participant.
3. If the chosen participant has only one match, I pair them and let them work together in part 3.
4. If the chosen participant has more than one match, I randomly choose one of the matches.
5. I exclude two participants that have been paired and repeat (1)-(3) until no feasible match is left.
6. If some participants are still left unpaired, I pair them up randomly.

### Part 3: Group work stage

The paired participants work together on the puzzles by alternating their moves for 12 minutes and earn 1€ for each puzzle solved. Which participant makes the first move is randomized at each puzzle, and this is told to both participants as in part 2. They can solve as many puzzles as possible with increasing difficulty (maximum 20 puzzles).

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11. Solving the puzzle itself is not incentivized, and thus participants who do not want to collaborate with the paired participant or fear to receive a bad response may not reverse that participant’s move even if they think the move is wrong. However, since I am interested in the effect of correction on collaborator selection, participants’ *intention* to correct that does not end up as an actual correction does not confound the analysis.

12. All the texts are in Italian in the experiment.

## Post-experiment

Each participant answers a short questionnaire which consists of (i) the six hostile and benevolent sexism questions used in Stoddard, Karpowitz, and Preece (2020) with US college students and (ii) their basic demographic information and what they have thought about the experiment.<sup>13</sup> The answer to their demographic information is used to know participants' characteristics as well as casually check whether they have anticipated that the experiment is about gender, for which I do not find any evidence.

After participants answer all the questions, I tell them their earnings and let them leave the virtual room and Zoom. They receive their earnings via PayPal.

## 2.2 Implementation

The experiment was programmed with oTree (Chen, Schonger, and Wickens 2016) and conducted in Italian during November-December 2020. I recruited 464 participants (244 female and 220 male) registered on the Bologna Laboratory for Experiments in Social Science's ORSEE (Greiner 2015) who (i) were students, (ii) were born in Italy, and (iii) had not participated in gender-related experiments before (as far as I could check).<sup>14</sup> The first two conditions were to reduce noise coming from differences in socio-demographic backgrounds and race or/and ethnicity that may be inferred from participants' first name or/and voice, and the last condition was to reduce experimenter demand effects.<sup>15</sup> The number of participants was determined by a power simulation in the pre-analysis plan to achieve 80% power.<sup>16</sup> The experiment is pre-registered with the OSF.<sup>17</sup>

I ran 29 sessions with 16 participants each. The average duration of a session was 70 minutes. The average total payment per participant was 11.55€ with a maximum of 25€ and a minimum of 2€, all including the 2€ show-up fee. Table 1 describes the participants' characteristics. The table shows that female participants are slightly younger (1.41 years) and less gender-biased (0.12). In addition, female participants are more likely to major in humanities, and male participants are more likely to major in natural sciences and engineering, a tendency observed in most OECD countries (see, for example, Carrell, Page, and West 2010).<sup>18</sup> Also, most female and male participants are either bachelor's or master's students (97% female and 94% male), and only a few are PhD students.<sup>19</sup>

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13. I was planning to use a gender bias measure constructed from the hostile and benevolent sexism questions to show those with higher gender bias respond more negatively to women's corrections. However, people do not respond more negatively to women's corrections and that I could not have enough variation in this gender bias measure, so decided not to report it in the main text; the results are reported in Appendix B.

14. The laboratory prohibits deception, so no participant has participated in an experiment with deception.

15. Despite that I recruited only Italy-born people, 1 male participant answered in the post-questionnaire that he was from abroad. I include this participant in the analysis anyway but the results are robust to excluding this participant from the data.

16. This number includes 16 participants from a pilot session run before the pre-registration, where the experimental instructions were slightly different. The results are robust to the exclusion of these 16 participants.

17. The pre-registration documents are available at the OSF registry: <https://osf.io/tgyc5>.

18. Individual fixed effects in the analysis control for one's major. However, I do not run heterogeneity analysis by major because the major choice is endogenous to one's gender.

19. No economics PhD student participated in the experiment.



Table 1: Participants' characteristics

	Female (N=244)			Male (N=220)			Difference (Female – Male)	
	Mean	SD	Median	Mean	SD	Median	Mean	P-value
Age	24.45	3.13	24	25.87	4.33	25	-1.41	0.00
Gender bias	0.17	0.16	0.12	0.29	0.19	0.29	-0.12	0.00
Region of origin (within Italy)								
North	0.32			0.36			-0.04	0.37
Center	0.23			0.24			-0.01	0.77
South	0.45			0.40			0.06	0.23
Major:								
Humanities	0.45			0.22			0.23	0.00
Social sciences	0.24			0.27			-0.03	0.52
Natural sciences	0.12			0.20			-0.08	0.02
Engineering	0.05			0.23			-0.17	0.00
Medicine	0.13			0.08			0.05	0.08
Program:								
Bachelor	0.34			0.26			0.08	0.06
Master	0.63			0.68			-0.05	0.26
Doctor	0.03			0.06			-0.03	0.11

*Notes:* This table describes participants' characteristics. P-values of the difference between female and male participants are calculated with heteroskedasticity-robust standard errors.

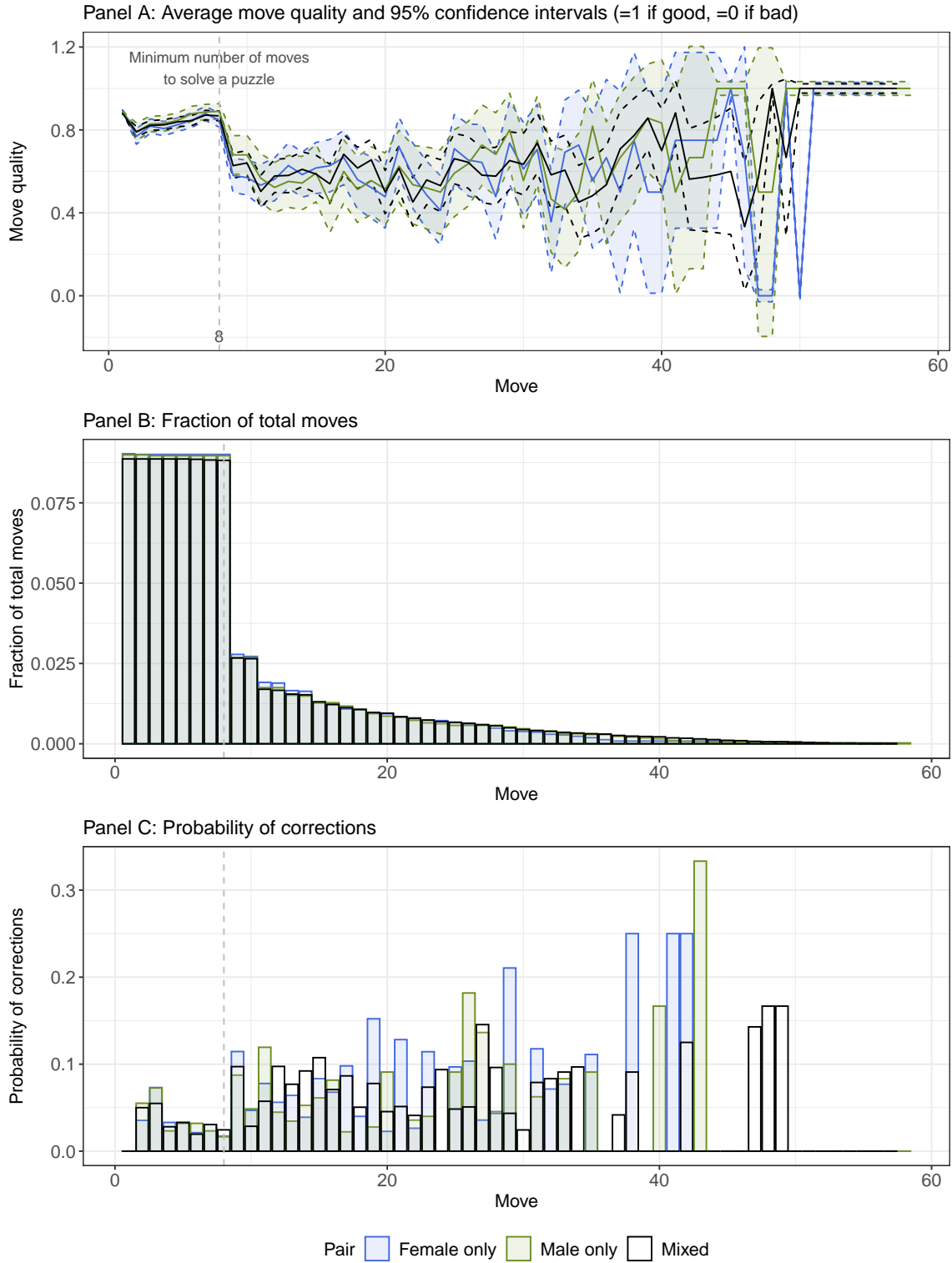
### 3 Data description

I use part 2 data in the analysis as part 2 is where we can observe collaborator selection decisions. I aggregate the move-level data at each puzzle so that we can associate behaviors in the puzzle to the collaborator selection decisions.

#### 3.1 Move-level data

Figure 3 shows average move quality across moves along with 95% confidence bands (Panel A), fraction of total moves (Panel B), and probability that a correction is happening (Panel C), for female only pairs (blue), male only pairs (green), and mixed gender pairs (black-white). Panel A shows no statistically significant differences in move quality by own gender or the gender of the partner. Panel B shows that about 71% of the puzzles are solved within a minimum number of moves (the minimum number of moves is 8) and shows that own gender or the gender of the partner does not matter in how fast participants solve the puzzle. Panel C shows that corrections happen across the moves, but there are no systematic differences in the probability that correction is happening by own gender or the gender of the partner.

Figure 3: Move quality, the fraction of total moves, and probability of corrections

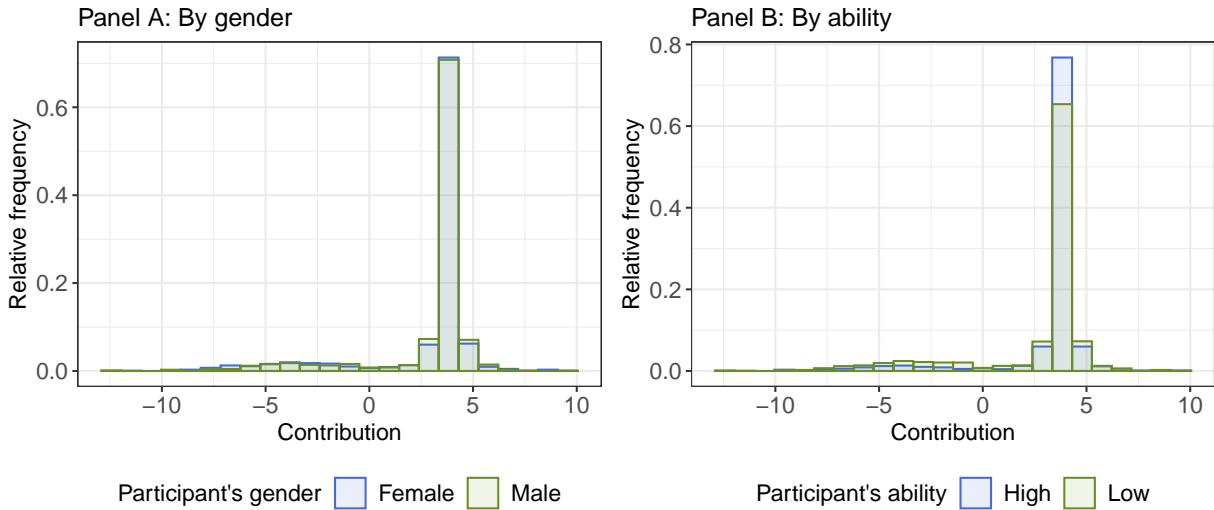


Notes: The average move quality along with 95% confidence intervals (panel A), the fraction of total moves in each move (panel B), and the probability of corrections in each move (panel C), separately for female only (gray), male only (white), and mixed gender pairs (blue). The confidence interval of panel A is 95% confidence intervals of  $\beta$ s from the following OLS regression:  $MoveQuality_{ijt} = \beta_1 + \sum_{k=2}^{58} \beta_k \mathbb{1}[t_{ij} = k] + \epsilon_{ijt}$ , where  $t_{ij}$  is the pair  $i$ - $j$ 's move round and  $\mathbb{1}$  is an indicator variable.  $MoveQuality_{ijt}$  takes a value of 1 if a move of a pair  $i$ - $j$  in  $t$ th move is good and 0 if bad. I add an estimate of  $\beta_1$  to estimates of  $\beta_2$ - $\beta_{58}$  to make the figure easier to look at. Standard errors are clustered at the pair level.

### 3.2 Puzzle-level data

Table 2 describes own (panel A) and partner’s puzzle behaviors (panel B) and puzzle outcomes (panel C). Panel A shows no gender differences in puzzle-solving ability: both contribution in part 2 and the number of puzzles solved in part 1, the difference between female and male participants are statistically insignificant at 5% and quantitatively insignificant.<sup>20,21</sup> This is consistent with Isaksson (2018), who also finds no gender difference in contribution or number of puzzles solved alone using the same puzzle, suggesting that any gender difference I would find is unlikely to come from their ability difference. Panel A also shows that there are no gender differences in propensity to correct partners, unlike Isaksson (2018), who finds that men correct their partner more often than women, although their result is from move-level data. Finally, the last row of Panel A shows that male participants are slightly more likely to face female partners, although only three percentage points more.

Figure 4: Distribution of contribution



*Notes:* This figure shows the distribution of individual contribution by gender (panel A) and ability (panel B) and shows that most participants contributed to the same degree. Panel A further shows no gender difference in contribution, and panel B further shows that among high-ability people, a higher fraction contributes to the same degree. Contribution is defined as one’s net good moves in a given puzzle (the number of good moves minus the number of bad moves).

To further elaborate on panel A of Table 2, Panel A of Figure 4 presents the distribution of contribution by participants’ gender that women and men are equally good at puzzle-solving: in about 70% of the puzzles, participants’ contribution is 4 (total good moves minus total bad moves), and women’s and men’s distributions almost overlap.

Panel B shows that puzzle-solving ability as well as propensity to make corrections (both of a mistake and a right move) of partners paired with female and male participants is the same,

20. The number of puzzles solved in part 1 is marginally significant but quantitatively insignificant.

21. The correlation coefficient between contribution and number of puzzles solved in part 1 is 0.1059 and the p-value is below 0.001 (with standard errors clustered at individual level).

Table 2: Own and partners' puzzle behaviors and puzzle outcomes

	Female (N=1708)		Male (N=1540)		Difference (Female – Male)		
	Mean	SD	Mean	SD	Mean	SE	P-value
<u>Panel A: Own behaviors</u>							
Contribution	2.98	2.93	3.14	2.64	-0.16	0.10	0.11
# puzzles solved in part 1	8.36	2.41	8.80	2.34	-0.44	0.22	0.05
Any correction	0.15	0.36	0.16	0.36	0.00	0.01	0.85
Good correction	0.12	0.33	0.12	0.33	0.00	0.01	0.90
Bad correction	0.06	0.23	0.05	0.22	0.00	0.01	0.70
(Fraction of female partners)	0.51	0.50	0.54	0.50	-0.03	0.02	0.03
<u>Panel B: Partner's behaviors</u>							
Contribution	3.04	2.73	3.07	2.87	-0.03	0.10	0.77
# puzzles solved in part 1	8.58	2.35	8.57	2.43	0.01	0.16	0.93
Any correction	0.16	0.37	0.15	0.36	0.01	0.01	0.51
Good correction	0.13	0.33	0.12	0.32	0.01	0.01	0.44
Bad correction	0.06	0.23	0.05	0.22	0.01	0.01	0.44
<u>Panel C: Puzzle outcomes</u>							
Willing to collaborate (yes=1, no=0)	0.72	0.45	0.71	0.45	0.01	0.02	0.49
Time spent (second)	43.74	36.15	42.99	35.76	0.74	1.28	0.56
Total moves	11.18	7.46	11.21	7.70	-0.03	0.28	0.92
Puzzle solved	0.85	0.36	0.86	0.35	-0.01	0.01	0.43
Consecutive correction	0.04	0.20	0.04	0.21	0.00	0.01	0.81

*Notes:* This table describes own (panel A) and partner's puzzle behaviors (panel B) and puzzle outcomes (panel C). P-values of the difference between female and male participants are calculated with standard errors clustered at the individual level. Contribution is defined as one's net good moves in a given puzzle (the number of good moves minus the number of bad moves).

suggesting random pairing was successful and that any gender differences I would find are not coming from partners of either gender correct more often. Participants are corrected by their partner in 15-16% of the total puzzles, of which 12-13% are good corrections, and 5-6% are bad corrections, and there are no gender differences in propensity to be corrected.<sup>22</sup>

Panel C shows that participants state they want to collaborate with the partner 71-72% of the time. Participants spend on average 43-44 seconds for each puzzle (the maximum time a pair can spend is 120 seconds) and take 11 moves. 85-86% of the puzzles are solved, and participants and the partner correct each other's move consecutively in 4% of the puzzles.<sup>23</sup> There is no gender difference in any of these outcomes, suggesting any gender differences cannot be attributed to the imbalance

22. The percentage of good corrections and bad corrections do not sum up to the percentage of any correction means there are puzzles where both good and bad corrections occurred. The results are robust to exclusion of these overlapping puzzles, as shown in Figures 6, 7, and 8.

23. Indeed, in puzzles where consecutive correction happens, probability of selecting a paired participant as collaborator drops from 78.0% to 26.8%.

in these outcomes.<sup>24</sup>

### 3.3 Across-round balance

Figure 5 plots average partner gender balance (fraction of female partners, panel A) and puzzle outcomes (panels B-H) across seven rounds along with their 95% confidence intervals (relative to round 1), separately for female (blue) and male participants (green).

First, there is some unbalance in partner's gender across rounds between female and male participants (Panel A), with female/male participants more/less likely to be paired with a female partner in round 1, but the difference is not statistically significant for rounds 2-7.

Second, there are no systematic gender differences in puzzle outcomes across rounds (Panels B-H), suggesting that female and male participants behave similarly across rounds. One difference could be good and bad corrections, with female participants making slightly more bad corrections and slightly fewer good corrections. However, as shown in Table 2, these differences are statistically insignificant.

Last, we see that in rounds 6 and 7, participants are less willing to collaborate, experience more corrections, and are less likely to solve the puzzle. Although they are all outcomes of a particular pair that is randomly formed, they can simply be correlations. Still, one may wonder whether rounds 6 and 7 are driving the results. I will show in section 7 that the results are robust to the exclusion of these rounds.

## 4 Theoretical framework

I present a simple theoretical framework to provide a rational agent's benchmark behaviors.

I consider a rational agent  $i$  who maximizes their expected payoff in a given round  $t$  by deciding whether they are willing to collaborate with a potential collaborator  $j$  with whom they have just played one puzzle, conditional on the history of decisions  $i$  has made to other potential collaborators with whom they have played the puzzle up to the current round  $t$  and with whom they will play the puzzle in the future rounds. Since with whom to be paired in which order is randomized, I simply denote the history and the future by  $t$ , consider them as exogenous, and normalize the payoff of not willing to collaborate with  $j$  as 0 for each round  $t$ .

The payoff is increasing in  $i$ 's belief about  $j$ 's ability. I assume  $i$  can partially observe  $j$ 's move quality, so  $i$ 's belief about  $j$ 's ability is increasing in  $j$ 's ability perceived by  $i$ .

Thus,  $i$  would face the following problem:

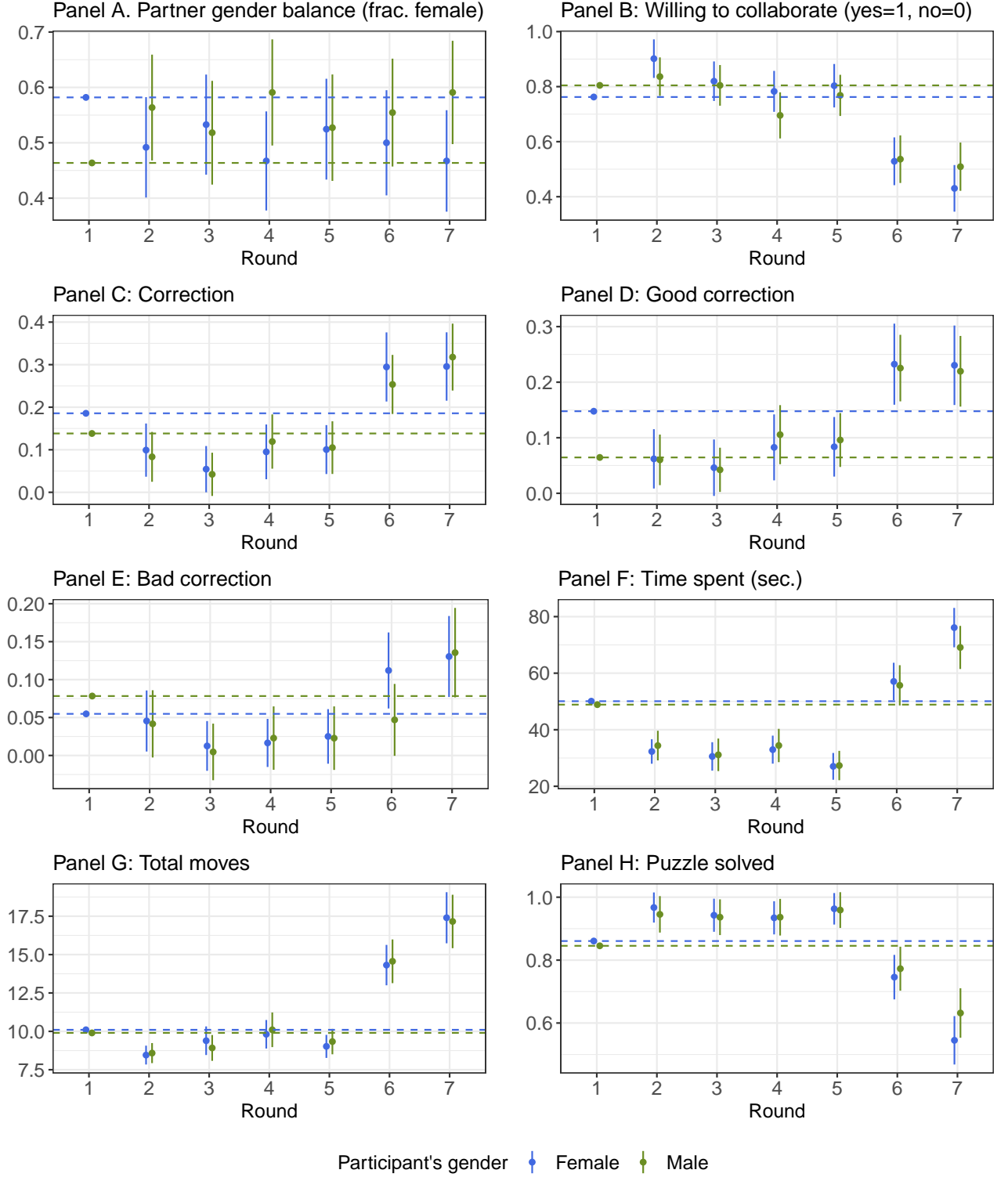
$$\max_{Accept \in \{0,1\}} \mathbb{1}[Accept = 1] \times E_{\mu_j}[\pi_t(\mu_j(\tilde{a}_j, c_j^q, f_j)) | \theta, \omega, t], \quad \partial \pi_t / \partial \mu_j > 0, \quad \partial \mu_j / \partial \tilde{a}_j > 0 \quad (1)$$

where each term is defined as follows:

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24. Note that time spent to solve a puzzle is endogenous to correction and not a good control. For example. if one corrects a mistake, then it takes fewer time to solve the puzzle. If one corrects a right move, on the other hand, then it takes more time to solve the puzzle.

Figure 5: Balance across rounds



*Notes:* This figure shows point estimates and 95% confidence intervals of  $\beta_s$  from the following OLS regression with gender balance (female dummy) and different puzzle outcomes separately for female (blue) and male participants (green):  $y_{ij} = \beta_1 + \sum_{k=2}^7 \beta_k \mathbb{1}[t_{ij} = k] + \epsilon_{ij}$ , where  $t_{ij} \in \{1, 2, 3, 4, 5, 6, 7\}$  is the puzzle round in which  $i$  and  $j$  are playing,  $\mathbb{1}$  is an indicator variable, and  $y_{ij}$  is the dependent variable indicated in each panel. I add the estimate of  $\beta_1$  to estimates of  $\beta_2$ - $\beta_7$  to make the figure easier to look at. Standard errors are clustered at the individual level.

- *Accept*: whether  $i$  is willing to collaborate with  $j$  (=0 if no, =1 if yes)
- $\mu_j$ :  $i$ 's belief about  $j$ 's ability
- $\tilde{a}_j$ :  $j$ 's ability perceived by  $i$
- $c_j^q$ :  $j$ 's correction (=1 if  $j$  corrected  $i$ , =0 if  $j$  did not correct  $i$ ), which is either good ( $q = g$ ) or bad ( $q = b$ ).
- $f_j$ :  $j$ 's gender (=1 if female, =0 if male)
- $\theta$ :  $i$ 's belief about their ability relative to other participants in the session (>0 if higher, =0 if same, <0 if lower)
- $\omega$ :  $j$ 's belief about women's ability relative to men (>0 if higher, =0 if same, <0 if lower)

where  $\mathbb{1}$  is an indicator function. Although  $\theta$  and  $\omega$  could depend on  $t$ , I omit the dependence on  $t$  for simplicity because  $t$  is exogenous.

If  $i$  can fully observe  $j$ 's move quality and  $i$  is fully rational, then  $c_j^q$  ( $q = g, b$ ) and  $f_j$  do not convey any information about  $j$ 's ability and is irrelevant for  $i$ 's decision making. This is true regardless of whether the correction is good or bad. However, since  $i$  can only partially observe  $j$ 's move quality,  $j$ 's correction and gender convey information about  $j$ 's ability even if  $i$  is fully rational.<sup>25</sup>

First, keeping  $j$ 's ability perceived by  $i$  fixed, the information  $j$ 's correction conveys depends on  $\theta$ . If  $i$  believes they are good at the puzzle, they would consider a correction as a signal of low ability because  $i$  believes their move is correct. On the other hand, if  $i$  believes their ability is low, then they would consider a correction as a signal of high ability. If  $i$  believes their ability is the same as  $j$ 's, then a correction would not convey any information.

However, since  $i$  can partially observe  $j$ 's move quality,  $i$  considers a good correction as a less negative/more positive signal than a bad correction regardless of  $\theta$ . Thus, we have the following proposition:

**Proposition 1.** *A rational agent  $i$  is less willing to collaborate with  $j$  when  $j$  made a bad correction than when  $j$  made a good correction, regardless of  $i$ 's belief about their own ability. That is:*

$$\partial \mu_j / \partial c_j^b < \partial \mu_j / \partial c_j^g \quad \forall \theta \quad (2)$$

Also, the more the  $i$  understands the puzzle, the more they can observe  $j$ 's move quality, hence corrections, regardless of  $\theta$ . Thus, we have the following proposition:

**Proposition 2.** *A rational agent  $i$  with high puzzle-solving ability is more willing to collaborate with  $j$  when  $j$  made a good correction and less willing to collaborate with  $j$  when  $j$  made a bad correction, compared to another rational agent with low puzzle-solving ability. This is true regardless*

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25. I nonparametrically control for  $j$ 's gender, but I also examine the effect of interaction term between  $j$ 's correction and  $j$ 's gender.

of their belief about their own ability. That is:

$$\begin{aligned}\partial\mu_j/\partial c_j^g|_{i's \text{ ability is high}} &> \partial\mu_j/\partial c_j^g|_{i's \text{ ability is low}} \forall \theta \\ \partial\mu_j/\partial c_j^b|_{i's \text{ ability is high}} &< \partial\mu_j/\partial c_j^b|_{i's \text{ ability is low}} \forall \theta\end{aligned}\tag{3}$$

Similar to the response to corrections, if  $i$  believes women are better at the puzzle, they would consider a correction from a woman as a signal of high ability relative to men's correction. On the other hand, if  $i$  believes women is worse at the puzzle, then they would consider a correction from a woman as a signal of low ability relative to men's correction. If  $i$  believes women and men are equally good at the puzzle, then a correction from a woman or man is irrelevant. Thus, we have the following proposition:

**Proposition 3.** *A rational agent  $i$ 's willingness to collaborate with  $j$  when  $j$  was a woman and made a correction relative to when  $j$  was a man and made a correction depends on their belief about women's ability relative to men's. This is true regardless of  $i$ 's belief about their own ability and holds for both good and bad corrections. That is:*

$$\begin{aligned}\partial^2\mu_j/\partial c_j^g\partial f_j &> 0 \forall \theta, q \text{ if } \omega > 0 \\ \partial^2\mu_j/\partial c_j^g\partial f_j &< 0 \forall \theta, q \text{ if } \omega < 0\end{aligned}\tag{4}$$

In particular, if they believe women and men have the same ability, then  $j$ 's gender does not matter. That is:

$$\partial^2\mu_j/\partial c_j^g\partial f_j = 0 \forall \theta, q \text{ if } \omega = 0\tag{5}$$

I consider deviations from these propositions are evidence of non-rationality.

## 5 Empirical strategy

### 5.1 Response to corrections

To examine whether the data is consistent with Proposition 1, I estimate the following model with OLS.

$$Select_{ij} = \beta_1 CorrectedGood_{ij} + \beta_2 CorrectedBad_{ij} + \beta_3 Female_j + \delta Contribution_j + \mu_i + \epsilon_{ij}\tag{6}$$

where each variable is defined as follows:

- $Select_{ij} \in \{0, 1\}$ : an indicator variable equals 1 if  $i$  selects  $j$  as their collaborator, 0 otherwise.
- $CorrectedGood_{ij} \in \{0, 1\}$ : an indicator variable equals 1 if  $j$  corrected  $i$  and moved the puzzle closer to the solution, 0 otherwise.
- $CorrectedBad_{ij} \in \{0, 1\}$ : an indicator variable equals 1 if  $j$  corrected  $i$  and moved the puzzle far away from the solution, 0 otherwise.
- $Female_j \in \{0, 1\}$ : an indicator variable equals 1 if  $j$  is female, 0 otherwise.



- $Contribution_j \in \mathbb{Z}$ :  $j$ 's contribution to a puzzle played with  $i$ .
- $\epsilon_{ij}$ : omitted factors that affect  $i$ 's likelihood to select  $j$  as their collaborator.

and  $\mu_i \equiv \sum_{k=1}^N \mu^k \mathbb{1}[i = k]$  is individual fixed effects, where  $N$  is the total number of participants in the sample and  $\mathbb{1}$  is the indicator variable. Standard errors are clustered at the individual level.<sup>26</sup>

The key identification assumption is that  $Contribution_j$  fully captures  $j$ 's ability perceived by  $i$  through  $j$ 's puzzle moves (not true ability). This assumption is reasonable if we think participants' willingness to collaborate is increasing in the partner's contribution to the puzzle, which is consistent with that participants can partially observe their partners' ability and their expected utility is increasing in their payoff.

The identification discussion deserves a further elaboration: by the random pairing of participants, the paired participant's gender is exogenous to the participant's unobservables. However, correction is not exogenous for two reasons: (i) correction can be correlated with the paired participant's ability and paired participant's ability can affect the participant's collaborator selection; (ii) There is an effect similar to the reflection effect: participant's puzzle behavior affects the paired participant's behavior and vice versa. For example, a participant's meanness can increase the paired participant's correction and can also affect their collaborator selection. The identification assumption concerns the former point. To address the latter point, I add individual fixed effects.

Also, as discussed in the theoretical framework (Section 4), good and bad corrections only have a signaling effect on  $j$ 's ability after controlling for contribution; if  $i$  can fully observe  $j$ 's ability, good and bad corrections convey no information that a rational agent cares about.

## 5.2 Heterogeneity by participants' ability

To examine whether the data is consistent with Proposition 2, I estimate the following model with OLS.

$$\begin{aligned} Select_{ij} = & \beta_1 CorrectedGood_{ij} + \beta_2 CorrectedBad_{ij} + \beta_3 Female_j \\ & + \beta_4 CorrectedGood_{ij} \times HighAbility_i + \beta_5 CorrectedBad_{ij} \times HighAbility_i \\ & + \delta_1 Contribution_j + \delta_2 Contribution_j \times HighAbility_i + \mu_i + \epsilon_{ij} \end{aligned} \quad (7)$$

where each variable is defined as follows:

- $HighAbility_i \in \{0, 1\}$ : an indicator variable equals 1 if  $i$  solved the above-median number of puzzles in part 1 in a session they have participated, 0 otherwise.

Other variables are as defined in equation 6.

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26. This is because the treatment unit is  $i$ . Although the same participant appears twice (once as  $i$  and once as  $j$ ),  $j$  is passive in collaborator selection.

### 5.3 Heterogeneity by partners' gender

To examine whether the data is consistent with Proposition 3, I estimate the following model with OLS.

$$\begin{aligned} Select_{ij} = & \beta_1 CorrectedGood_{ij} + \beta_2 CorrectedBad_{ij} + \beta_3 Female_j \\ & + \beta_4 CorrectedGood_{ij} \times Female_j + \beta_5 CorrectedBad_{ij} \times Female_j \\ & + \delta_1 Contribution_j + \delta_2 Contribution_j \times Female_j + \mu_i + \epsilon_{ij} \end{aligned} \quad (8)$$

Where each variable is defined as in equation 6.

## 6 Results

### 6.1 Response to corrections

Table 3: Response to corrections

Dependent variable:	Willing to collaborate (yes=1, no=0)									
Sample:	All				Female				Male	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Good correction	-0.208*** (0.028)	-0.238*** (0.030)		-0.204*** (0.024)	-0.269*** (0.043)		-0.229*** (0.033)	-0.197*** (0.040)		-0.168*** (0.036)
Bad correction	-0.518*** (0.031)	-0.508*** (0.034)		-0.100*** (0.036)	-0.550*** (0.044)		-0.172*** (0.047)	-0.457*** (0.050)		-0.011 (0.052)
Any correction			-0.198*** (0.022)			-0.237*** (0.030)			-0.152*** (0.031)	
Female partner	-0.003 (0.016)	-0.001 (0.017)	0.008 (0.014)	0.009 (0.014)	-0.009 (0.021)	0.002 (0.018)	0.004 (0.018)	0.007 (0.026)	0.016 (0.021)	0.016 (0.021)
Partner's contribution			0.083*** (0.003)	0.084*** (0.003)		0.090*** (0.004)	0.089*** (0.004)		0.077*** (0.003)	0.080*** (0.004)
Individual FE		✓	✓	✓	✓	✓	✓	✓	✓	✓
P-value: Good correction =Bad correction	0.000	0.000		0.020	0.000		0.347	0.000		0.016
Baseline mean	0.780	0.780	0.780	0.780	0.780	0.780	0.780	0.778	0.778	0.778
Baseline SD	0.414	0.414	0.414	0.414	0.414	0.414	0.414	0.416	0.416	0.416
Adj. R-squared	0.104	0.100	0.334	0.335	0.111	0.365	0.369	0.090	0.306	0.306
Observations	3180	3180	3180	3180	1670	1670	1670	1510	1510	1510
Individuals	464	464	464	464	244	244	244	220	220	220

*Notes:* This table presents the regression results of equation 6. Columns 1-4 include all participants' willingness to collaborate, but column 1 excludes the partner's contribution and individual fixed effects and column 2 partner's contribution. Column 3 combines good and bad correction as a single dummy variable. Columns 5-7 present the corresponding results for women and columns 8-10 for men. Baseline mean and standard deviation are participants' willingness to collaborate with partners who do not make any corrections. Standard errors in parentheses are clustered at the individual level. Significance levels: \* 10%, \*\* 5%, and \*\*\* 1%.

Table 3 presents the regression results of equation 6. Columns 1-4 include all participants' willingness to collaborate, but column 1 excludes partner's contribution and individual fixed effects and column 2 partner's contribution. Column 3 combines good and bad correction as a single dummy variable. Columns 5-7 present the corresponding results for women and columns 8-10 for men.

Column 1 shows that when we do not control for between-participants variation, the coefficient

estimate on good correction is underestimated. Column 2 shows that when we do not control for the partner's contribution, the coefficient estimate on bad correction is negative and very large: the point estimate is -0.508 (p-value < 0.01); that is, participants are 50.8% less willing to collaborate with partners who made a bad correction, a correction that moved the puzzle far away from the solution. Indeed, these coefficient estimates are more negative than the coefficient estimates on good corrections: 0.271 more negative (p-value < 0.01). This is true when we separately examine women (column 5, 0.281 with p-value < 0.01) and men (column 8, 0.281 with p-value < 0.01).

Corroborating this, looking at column 3, the coefficient estimate on the partner's contribution is positive and quantitatively and statistically highly significant and is 0.083 (p-value < 0.01). This suggests that participants are 8.3% more willing to collaborate with partners who make one more good move. This is true for women (column 6, 0.090 with p-value < 0.01) and men (column 9, 0.077 with p-value < 0.01). This is evidence that my experimental design is valid: participants correctly understand the notion of good and bad moves and are more willing to collaborate with partners who contributed more.

The coefficient estimate on any correction in column 3 is negative and quantitatively and statistically highly significant and is -0.198 (p-value < 0.01). This suggests that people are 19.8% less willing to collaborate with those who made a correction(s). To offset this effect, a partner's contribution has to increase by 0.79 standard deviations.<sup>27</sup> The corresponding coefficient estimate for women is -0.237 (column 6, p-value < 0.01) and -0.152 for men (column 9, p-value < 0.01). Thus, participants are less willing to collaborate with a person who corrected their move.

This is not a problem if participants are more willing to collaborate with a person who made a good correction and less willing to collaborate with a person who made a bad correction. However, this is not the case: the coefficient estimate on good correction in column 4 is still negative and is -0.204 (p-value < 0.01). This suggests that people are less willing to collaborate even with those who made a good correction(s). The corresponding coefficient estimate for women is -0.229 (column 7, p-value < 0.01) and -0.168 for men (column 10, p-value < 0.01).

The coefficient estimate on bad correction in column 4 is also negative and quantitatively and statistically significant and is -0.100 (p-value < 0.01). However, the magnitude is smaller than the coefficient estimate on good correction: the difference is -0.104 (p-value < 0.05). This is mainly driven by men: the corresponding coefficient estimate for women is -0.172 (column 6, p-value < 0.01) but is -0.011 (p-value > 0.10) for men.

These behaviors are inefficient. They also seem to indicate deviation from the rational agent's benchmark in Proposition 1. However, response to corrections depends on the belief about people's own ability relative to partners and people are in general overconfident, albeit that men are more overconfident (Croson and Gneezy 2009). Thus, these behaviors may not be irrational.

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27. The number is calculated as follows:  $\hat{\beta}_{Partner's\ contribution} \times SD_{Partner's\ contribution} \times x = |\hat{\beta}_{Any\ correction}| \Rightarrow x = |\hat{\beta}_{Any\ correction}| / (\hat{\beta}_{Partner's\ contribution} \times SD_{Partner's\ contribution}) = 0.198 / (0.09 \times 2.8) \approx 0.79$ .  $SD_{Partner's\ contribution} = 2.8$  is from panel B of Table 2 and is an arithmetic average of 2.73 for partners faced by women 2.87 for and partners faced by men:  $(2.73 + 2.87) / 2 = 2.80$ .

## 6.2 Heterogeneity by participants' ability

Table 4: Response to corrections of high vs. low ability participants

Dependent variable:	Willing to collaborate (yes=1, no=0)					
Sample:	All		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Good correction		-0.155*** (0.030)		-0.208*** (0.042)		-0.107*** (0.041)
Bad correction		-0.100** (0.047)		-0.201*** (0.064)		0.005 (0.063)
Any correction	-0.153*** (0.028)		-0.213*** (0.041)		-0.096** (0.037)	
Female partner	0.008 (0.014)	0.009 (0.014)	0.002 (0.018)	0.002 (0.018)	0.015 (0.021)	0.014 (0.021)
Partner's contribution	0.084*** (0.003)	0.084*** (0.004)	0.090*** (0.005)	0.089*** (0.005)	0.079*** (0.004)	0.082*** (0.004)
Good correction x High ability		-0.118** (0.050)		-0.048 (0.066)		-0.180** (0.075)
Bad correction x High ability		0.000 (0.072)		0.074 (0.095)		-0.061 (0.109)
Any correction x High ability	-0.108** (0.044)		-0.051 (0.061)		-0.152** (0.064)	
Partner's contribution x High ability	-0.002 (0.005)	-0.001 (0.005)	-0.002 (0.007)	-0.001 (0.007)	-0.004 (0.007)	-0.003 (0.008)
Individual FE	✓	✓	✓	✓	✓	✓
Baseline mean	0.780	0.780	0.783	0.783	0.778	0.778
Baseline SD	0.414	0.414	0.413	0.413	0.416	0.416
Adj. R-squared	0.335	0.336	0.365	0.368	0.308	0.308
Observations	3180	3180	1670	1670	1510	1510
Individuals	464	464	244	244	220	220

*Notes:* This table presents the regression results of equation 8. Columns 1-2 include all participants' willingness to collaborate. Columns 3-4 present the corresponding results for women and columns 5-6 for men. Baseline mean and standard deviation are participants' willingness to collaborate with partners who do not make any corrections. Standard errors in parentheses are clustered at the individual level. Significance levels: \* 10%, \*\* 5%, and \*\*\* 1%.

Table 4 shows the negative response to corrections we observed in the previous subsection is likely to be irrational: the table presents the regression results of equation 8. As Table 3, columns 1-2 include all participants' willingness to collaborate. Columns 3-4 the corresponding results for women and columns 5-6 for men.

In column 1, the coefficient estimate on the interaction between any correction and high ability is negative and statistically significant (p-value < 0.05). This effect mainly comes from men: the corresponding coefficient estimate for women (column 3) is less negative and statistically insignificant but is more for men (column 5, p-value < 0.05). Thus, high-ability people, in particular men, dislike receiving corrections more than low-ability people.

It is not a problem if this result is coming from high-ability people responding less negatively or even positively to good corrections and more negatively to bad corrections. However, this is not

the case: in column 2, the coefficient estimate on the interaction between good correction and high ability is negative (p-value  $< 0.05$ ). This effect comes from both women and men, with the effect on men being stronger: the corresponding coefficient estimate for women (column 4) is negative, albeit less so and statistically insignificant and is more negative and statistically significant (p-value  $< 0.05$ ) for women (in column 6).

The coefficient estimate on the interaction between bad correction and high ability in column 2 is almost zero. The corresponding coefficient estimate is positive for women (column 4) and negative for men (column 6), although they are both statistically insignificant.

Thus, even high-ability participants respond negatively to good corrections, with men responding more negatively. This suggests that a negative reaction to corrections is likely to be irrational: as discussed at the beginning of this section, high-ability participants should be able to distinguish between good and bad corrections and should respond less negatively to good corrections and more negatively to bad corrections than low ability participants as the rational agent benchmark in Proposition 2 suggests. However, what we see here is the opposite.

### 6.3 Heterogeneity by partners' gender

Table 5 presents the regression results of equation 8. As Table 3, columns 1-2 include all participants' willingness to collaborate, columns 3-4 present the corresponding results for women and columns 5-6 for men.

Looking at column 1, the coefficient estimate on the interaction between the partner's contribution and female partner is almost 0 and statistically insignificant. Column 3 shows this is true for women and column 5 for men. These suggest that people – both women and men – do not underestimate women's contribution when selecting a collaborator. In other words, people correctly believe that women and men are equally good at solving puzzle.

In column 1, the coefficient estimate on the interaction between any correction and female partner is close to 0 and statistically insignificant. However, women and men respond differently: the corresponding coefficient estimate is positive for women (column 3) but negative for men (column 5), although they are statistically insignificant.

Column 2 splits any correction into good and bad correction and shows an asymmetric response: the coefficient estimate on the interaction between good correction and female partner is negative although statistically insignificant, but the coefficient estimate on the interaction between female partner and bad correction is positive (p-value  $< 0.05$ ).

The negative coefficient estimate on the interaction between good correction and female partner mainly comes from men: looking at column 6, the corresponding coefficient estimate for men is -0.119 and marginally significant (p-value  $< 0.10$ ), while for women it is 0.035 although statistically insignificant (column 4). On the other hand, the positive coefficient estimate on the interaction between female partner and bad correction comes from both women and men: the corresponding coefficient estimate is 0.090 for women (column 4) and 0.168 for men (column 6), although neither of them is statistically significant. Together with the evidence that men believe women are equally

Table 5: Response to corrections made by women vs. men

Dependent variable:	Willing to collaborate (yes=1, no=0)					
Sample:	All		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Good correction		-0.187*** (0.035)		-0.248*** (0.045)		-0.104* (0.053)
Bad correction		-0.176*** (0.051)		-0.218*** (0.064)		-0.104 (0.076)
Any correction	-0.203*** (0.031)		-0.260*** (0.042)		-0.125*** (0.045)	
Female partner	0.013 (0.022)	0.001 (0.022)	-0.001 (0.032)	-0.002 (0.032)	0.026 (0.029)	0.003 (0.030)
Partner's contribution	0.084*** (0.004)	0.083*** (0.004)	0.090*** (0.006)	0.089*** (0.006)	0.078*** (0.005)	0.077*** (0.006)
Good correction x Female partner		-0.035 (0.044)		0.035 (0.057)		-0.119* (0.067)
Bad correction x Female partner		0.144** (0.070)		0.090 (0.093)		0.168 (0.102)
Any correction x Female partner	0.009 (0.041)		0.047 (0.056)		-0.051 (0.059)	
Partner's contribution x Female partner	-0.002 (0.005)	0.002 (0.005)	-0.001 (0.008)	-0.001 (0.008)	-0.001 (0.007)	0.006 (0.007)
Individual FE	✓	✓	✓	✓	✓	✓
Baseline mean	0.780	0.780	0.783	0.783	0.778	0.778
Baseline SD	0.414	0.414	0.413	0.413	0.416	0.416
Adj. R-squared	0.333	0.336	0.365	0.369	0.305	0.307
Observations	3180	3180	1670	1670	1510	1510
Individuals	464	464	244	244	220	220

*Notes:* This table presents the regression results of equation 8. Columns 1-2 include all participants' willingness to collaborate. Columns 3-4 present the corresponding results for women and columns 5-6 for men. Baseline mean and standard deviation are participants' willingness to collaborate with partners who do not make any corrections. Standard errors in parentheses are clustered at the individual level. Significance levels: \* 10%, \*\* 5%, and \*\*\* 1%.

good at solving the puzzle as men, this is inconsistent with Proposition 3.

Men's less negative – or even positive – response to women's bad correction is a bit puzzling. One explanation is that men do not like to be corrected for their mistakes by women, but they are okay that women make mistakes.

Although only statistically marginally significant, men's negative reaction to women's good correction is worrying as men are still the majority in top positions both in industry (Bertrand 2018) and academia (Lundberg and Stearns 2019).

## 7 Robustness checks

### 7.1 Excluding unsolved puzzles

Whether participants can solve a puzzle is an outcome of a particular pairing that is random. However, “a good move is only preferable if you are playing with a partner who is also trying to

solve the puzzle” (Isaksson 2018, p. 25). If a participant is not trying to solve the puzzle, then a pair is unlikely to solve the puzzle and good and bad corrections may not be meaningful.

## 7.2 Excluding rounds 6 and 7

Remember that in rounds 6 and 7, participants’ willingness to collaborate is lower, they correct others more, and they are less likely to solve the puzzle, as shown in Figure 5 in section 3. As discussed in section 3, they are all outcomes of a particular pair independent of the type of the partner, but one may wonder whether these rounds are driving the results.

## 7.3 Excluding puzzles where good and bad corrections occurred

There are 495 puzzles in which at least one correction occurred, of which 325 puzzles experienced good corrections only, 110 puzzles bad corrections only, and 60 puzzles experienced both good and bad corrections. In these 60 puzzles, it is unclear which corrections – good or bad – dominated people’s minds in determining whether to collaborate with a paired person.

## 7.4 Robustness results

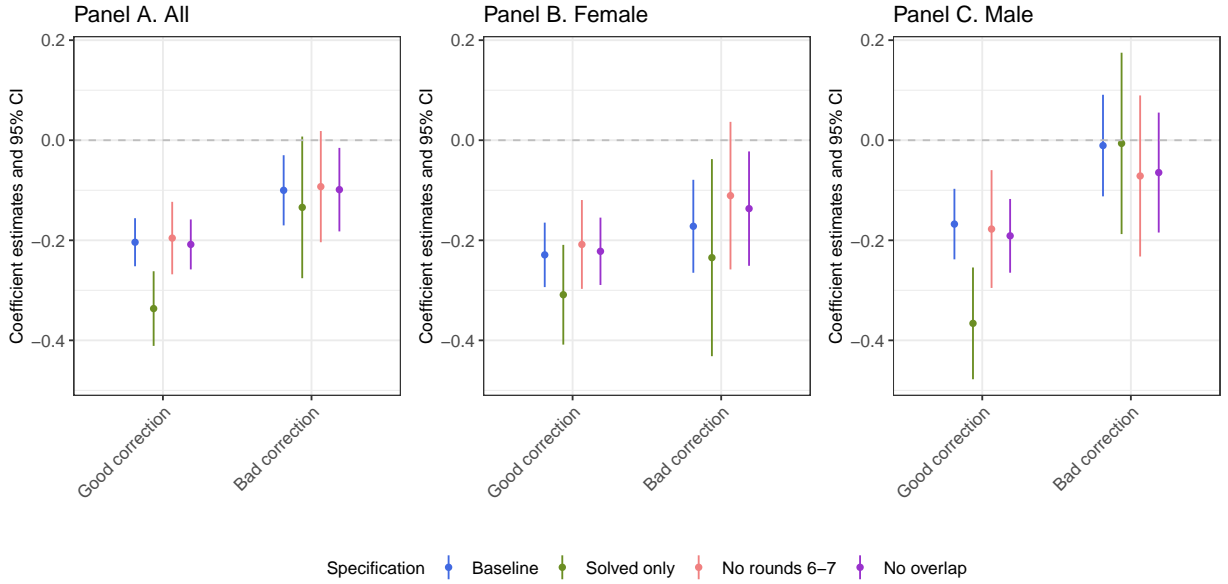
To address these concerns, I re-estimate equations 6, 7, and 8, and plot the coefficient estimates and 95% confidence intervals of the main coefficients of interest in Figures 6, 7, and 8, respectively, with solved puzzles only (green dots and lines), with rounds 1-5 only (red dots and lines), and with puzzles where only good or bad corrections occurred (purple dots and lines). As a reference, I also plot the coefficient estimates and 95% confidence intervals with the main sample used in Tables 3, 4, and 5 (blue dots and lines). All estimates are from the full models (columns 4, 7, and 10 for Table 3 and columns 2, 4, and 6 for Tables 4 and 5).

The main coefficients of interest for equation 6 are good and bad corrections. Looking at Figure 6, we see that most coefficient estimates are close to the main estimates. The estimates are more negative for good correction when the sample is limited to solved puzzles only, but they are more in line with the main findings.

The main coefficients of interest for equation 7 are the interaction between good correction and high ability and between bad correction and high ability. Looking at Figure 7, we again see most of the coefficient estimates are close to the main estimates.

The main coefficients of interest for equation 8 are the interaction between good correction and female partner and between bad correction and female partner. Looking at Figure 8, we again see most of the coefficient estimates are close to the main estimates. Again, the estimates with solved puzzles only present somewhat different evidence; in particular, response to good corrections by female partners is negative although statistically insignificant for women and positive for men. However, both estimates are very close to 0 and do not contradict that the evidence that men react more negatively to women’s good correction is only suggestive.

Figure 6: Response to corrections: Robustness



*Notes:* This figure plots the coefficient estimates and 95% confidence intervals of columns 4, 7, and 10 of Table 3 with solved puzzles only (the green dots and lines), with rounds 1-5 only (the red dots and lines), and with puzzles where only good or bad corrections occurred (the purple dots and lines). The blue dots and lines are the corresponding baseline estimates. They show that the findings in Table 3 are robust to limiting samples in these ways.

## 8 Conclusion

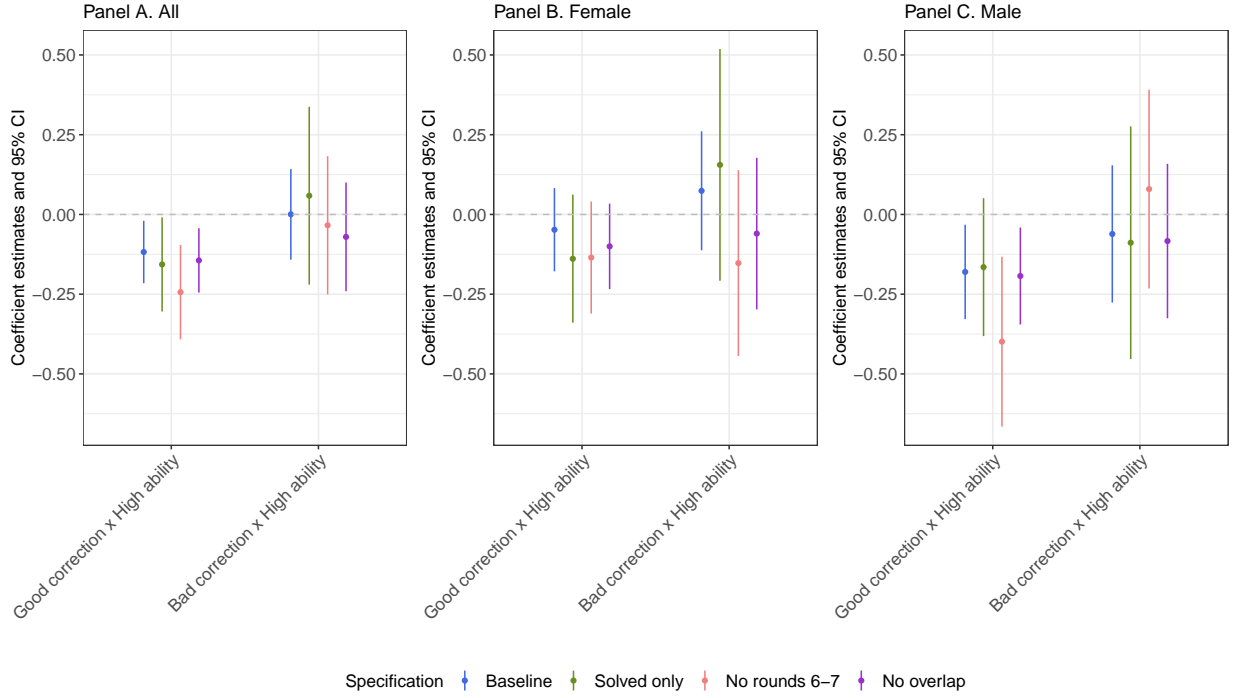
This paper demonstrates that people, including those with high productivity, are less willing to collaborate with someone who has corrected them even if the correction improved group performance. I also find suggestive evidence that men respond more negatively to women’s corrections that improves group performance, presumably because men do not like to be corrected for their mistakes by women. Thus, dislike to be corrected distorts the optimal selection of talents and penalizes those who correct others’ mistakes, and the distortion may be stronger when women correct men.

While a laboratory setting is different from the real world, my findings are likely to be a lower bound because of the following three reasons. First, there is no reputation cost in my experiment: being corrected is not observed by others, unlike in the real world. Second, the emotional stake is much smaller in my experiment: the puzzle ability is not informative of the ability relevant for their work or study – it is not something people have been devoting much of their time to, such as university exams, academic research, or corporate investment projects. Third, participants are equal in my experiment; in the real world, there are sometimes senior-junior relationships, and corrections by junior people may induce stronger negative reactions. Thus, introducing reputation cost, using tasks that are more related to one’s real-world ability, and having age variation would be interesting extensions of this paper.

But there are two limitations. The first is that participants are strangers to each other in my experiments, while people know each other in the real world. Thus, it is possible that repeated



Figure 7: Response to corrections made of high vs. low ability people: Robustness



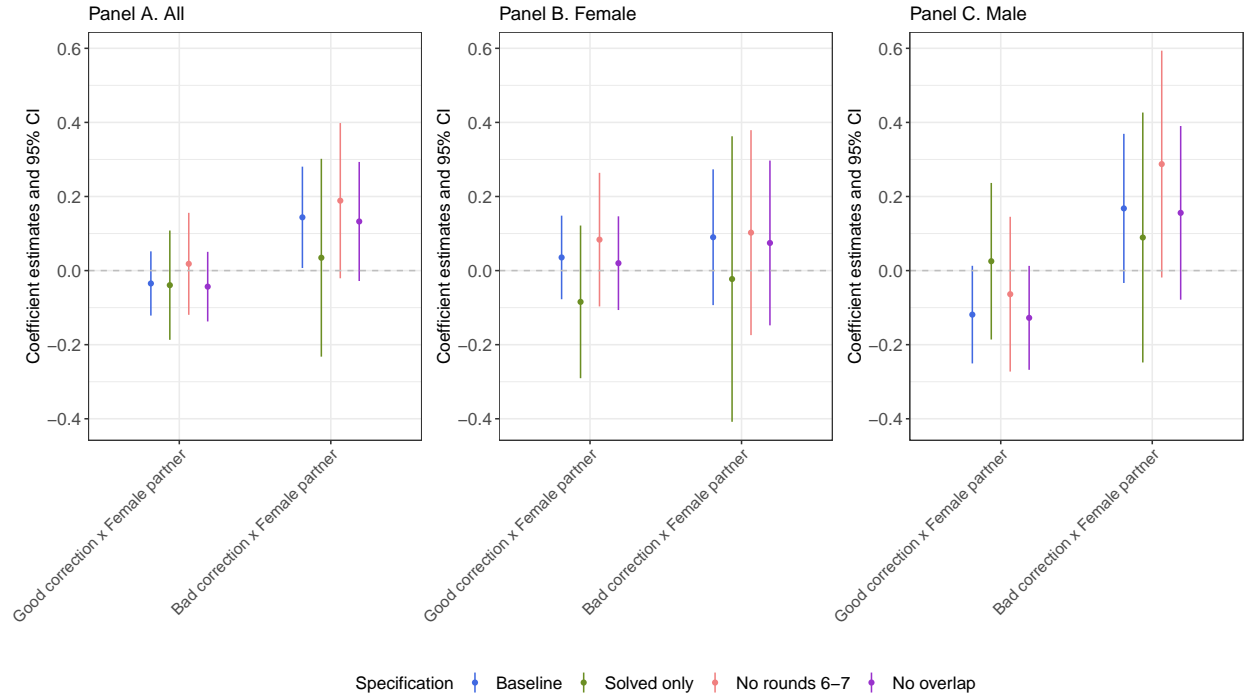
*Notes:* This figure plots the coefficient estimates and 95% confidence intervals of columns 2, 4, and 6 of Table 4 with solved puzzles only (the green dots and lines), with rounds 1-5 only (the red dots and lines), and with puzzles where only good or bad corrections occurred (the purple dots and lines). The blue dots and lines are the corresponding baseline estimates. They show that the findings in Table 4 are robust to limiting samples in these ways.

interactions would mitigate people's negative response to corrections (but they may also magnify the negative response due to rivalry, failure to build a good rapport, etc.). The second limitation is that most participants are bachelor's or master's students who are supposed to have a weaker gender bias. The first point relates to the takeaway of my results: it would be worth investigating whether a good workplace climate mitigates negative reactions to corrections. The second point relates to external validity: women's corrections may receive stronger and more robust negative reactions in the real world where people are older.

Finally, my experiment is not designed to investigate the underlying mechanism, but the results are consistent with self-image concerns and information avoidance. For example, Kszegi (2006) finds that people avoid a difficult task when it reveals their ability. Corroborating this, Castagnetti and Schmacker (2021) find people select information less informative about their ability, and Ewers and Zimmermann (2015) find people exaggerate their ability when others observe it even at the cost of reducing their payoff. Regarding gender, evidence suggests that people respond differently to women's and men's feedback (Sinclair and Kunda 2000). My results can be interpreted as that receiving good corrections is negative feedback, and accepting them as correct damages people's self-image.<sup>28</sup> Investigating how people's information avoidance affects workplace climates, the role

28. Which means  $\theta$  in the theoretical model in section 4 (equation 1) is not exogenous.

Figure 8: Response to corrections made by women vs. men: Robustness



*Notes:* This figure plots the coefficient estimates and 95% confidence intervals of columns 2, 4, and 6 of Table 5 with solved puzzles only (the green dots and lines), with rounds 1-5 only (the red dots and lines), and with puzzles where only good or bad corrections occurred (the purple dots and lines). The blue dots and lines are the corresponding baseline estimates. They show that the findings in Table 5 are robust to limiting samples in these ways.

of gender, and how to mitigate them would be an interesting avenue for future research.

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# Appendix

## Appendix A Advantages and drawbacks of quasi-laboratory format

The quasi-laboratory experimental format I use in this paper has advantages and drawbacks over the standard online and physical laboratory format.

**Over standard online format** The main advantage over standard online experimental format is that we can mostly avoid attrition, which is the main problem of online interactive experiments (Arechar, Gächter, and Molleman 2018). The reason is that compared to platforms such as MTurk and Prolific where participants’ identity is fully anonymous by their rule, we have participants’ personal information and participants know it as we recruit them from our standard laboratory subject pool. Also, they are connected to us via Zoom throughout the experiment. In my experiment, I experienced no participant attrition.

Another advantage is that we can fully control who will participate in the experiment. For instance, we can screen out participants who have participated in particular kinds of experiments, such as experiments involving deception, which is another problem of online experiments (Arechar, Gächter, and Molleman 2018). In my case, I have excluded participants who have participated in gender-related experiments in the past. This allows us to collect cleaner data.

The key drawback is the difficulty of collecting a large number of observations. Unlike MTurk or Prolific, the experimenter has to be present and respond to participants, if necessary, throughout the experiment. We could recruit a large number of participants at once, for example several hundred, but it weakens the connection between the experimenter and the participants and can induce attrition.

**Over physical laboratory format** The main advantage over physical laboratory format is logistical convenience both for the experimenter and the participants: we can run and join experiments from our offices or home as long as we have a computer and an internet connection. It primarily benefited me to comply with the COVID-19 precautions. However, it also means that we can run laboratory experiments even if we do not have a physical laboratory in our university, for example in universities in low-income countries, as long as we set up ORSEE (Greiner 2015) or other subject management systems, many of which are free.

Another advantage is that since participants can join the experiments from anywhere in the world, we can potentially run experiments with non-standard subjects or what Harrison and List (2004) call artefactual field experiments. For instance, non-student subjects or subjects in other countries. Although there can be regulation issues we have to overcome, it increases the kind of questions we can answer.

There are already a few studies that use a quasi-laboratory format, for example, Goeschl, Oestreich, and Soldà (2021).

## Appendix B Heterogeneity by gender bias

I have pre-specified in the pre-analysis plan that investigated heterogeneous responses to women’s corrections by the degree of gender bias measured by the six hostile and benevolent sexism questions used in Stoddard, Karpowitz, and Preece (2020), selected from Glick and Fiske (1996). Although I could not detect a meaningful variation, I present the results here.

I estimate the following model with OLS.

$$\begin{aligned} Select_{ij} = & \beta_1 CorrectedGood_{ij} + \beta_2 CorrectedBad_{ij} + \beta_3 Female_j \\ & + \beta_4 CorrectedGood_{ij} \times HighBias_i + \beta_5 CorrectedBad_{ij} \times HighBias_i \quad (B1) \\ & + \delta_1 Contribution_j + \delta_2 Contribution_j \times HighBias_i + \mu_i + \epsilon_{ij} \end{aligned}$$

where each variable is defined as follows:

- $HighBias_i \in \{0, 1\}$ : an indicator variable equals 1 if  $i$ ’s gender bias score from the six hostile and benevolent sexism questions is above median among participants with the same gender (female or male), 0 otherwise.

Other variables are as defined in equation 6.

Table B1 presents the regression results of equation B1. As Table 3, columns 1-2 include all participants’ willingness to collaborate. Columns 3-4 the corresponding results for women and columns 5-6 for men.

In columns 1, 3, and 5, the coefficient estimate on the interaction among any correction, female partner, and high bias is negative but statistically insignificant. Also, in columns 2, 4, and 6, the coefficient estimate on the interaction between good correction, female partner, and high bias as well as on the interaction between bad correction, female partner, and high bias is mostly negative but statistically insignificant. Thus, while the gender bias measure may detect some of the gender bias of participants, it is not variable enough to capture any meaningful heterogeneity among participants.

## Appendix C Results with the original contribution measure

In the main text, I changed the definition of contribution from the one in the pre-analysis plan because there was truncation in the original contribution measure in more than 10% of the puzzle. Nonetheless, the same results hold when I use the original contribution measure, reported in Tables C1, C2, C3, and C4. Although the original measure is relative to one’s pair while the measure I use in this paper is absolute, whether a measure is relative or absolute does not matter because I add individual fixed effects.

Table B1: Response to corrections made by women vs. men: Heterogeneity by gender bias

Dependent variable:	Willing to collaborate (yes=1, no=0)					
Sample:	All		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Good correction		-0.180*** (0.046)		-0.260*** (0.058)		-0.066 (0.071)
Bad correction		-0.196*** (0.071)		-0.185** (0.094)		-0.201* (0.104)
Any correction	-0.215*** (0.041)		-0.267*** (0.053)		-0.137** (0.065)	
Female partner	0.023 (0.029)	0.004 (0.029)	0.022 (0.039)	0.014 (0.040)	0.025 (0.041)	-0.006 (0.042)
Partner's contribution	0.088*** (0.006)	0.087*** (0.006)	0.094*** (0.008)	0.094*** (0.008)	0.082*** (0.007)	0.079*** (0.008)
Good correction x Female partner		-0.030 (0.060)		0.053 (0.080)		-0.151* (0.088)
Bad correction x Female partner		0.241** (0.096)		0.179 (0.127)		0.312** (0.143)
Any correction x Female partner	0.036 (0.055)		0.086 (0.076)		-0.044 (0.079)	
Partner's contribution x Female partner	-0.005 (0.007)	0.001 (0.008)	-0.007 (0.010)	-0.004 (0.010)	-0.002 (0.010)	0.007 (0.011)
Good correction x High bias		-0.018 (0.071)		0.027 (0.093)		-0.076 (0.106)
Bad correction x High bias		0.036 (0.100)		-0.069 (0.129)		0.173 (0.146)
Any correction x High bias	0.019 (0.063)		0.011 (0.089)		0.017 (0.091)	
Female partner x High bias	-0.027 (0.044)	-0.015 (0.044)	-0.050 (0.064)	-0.039 (0.065)	-0.010 (0.058)	0.008 (0.059)
Partner's contribution x High bias	-0.009 (0.008)	-0.008 (0.009)	-0.008 (0.012)	-0.010 (0.012)	-0.010 (0.010)	-0.006 (0.011)
Good correction x Female partner x High bias		-0.003 (0.089)		-0.025 (0.118)		0.060 (0.134)
Bad correction x Female partner x High bias		-0.177 (0.137)		-0.170 (0.186)		-0.257 (0.198)
Any correction x Female partner x High bias	-0.048 (0.082)		-0.073 (0.114)		-0.011 (0.118)	
Partner's contribution x Female partner x High bias	0.007 (0.011)	0.003 (0.011)	0.011 (0.016)	0.008 (0.016)	0.005 (0.014)	-0.000 (0.014)
Individual FE	✓	✓	✓	✓	✓	✓
Baseline mean	0.781	0.781	0.783	0.783	0.779	0.779
Baseline SD	0.414	0.414	0.413	0.413	0.415	0.415
Adj. R-squared	0.333	0.335	0.363	0.368	0.304	0.305
Observations	3173	3173	1670	1670	1503	1503
Individuals	463	463	244	244	219	219

*Notes:* This table presents the regression results of equation B1. Columns 1-2 include all participants willingness to collaborate. Columns 3-4 present the corresponding results for women and columns 5-6 for men. Baseline mean and standard deviation are participants' willingness to collaborate with partners who do not make any corrections. Standard errors in parentheses are clustered at the individual level. Significance levels: \* 10%, \*\* 5%, and \*\*\* 1%.

Table C1: Response to corrections: The original contribution measure

Dependent variable:	Willing to collaborate (yes=1, no=0)									
Sample:	All			Female				Male		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Good correction	-0.208*** (0.028)	-0.238*** (0.030)		-0.272*** (0.026)	-0.269*** (0.043)		-0.304*** (0.035)	-0.197*** (0.040)		-0.230*** (0.038)
Bad correction	-0.518*** (0.031)	-0.508*** (0.034)		-0.160*** (0.037)	-0.550*** (0.044)		-0.234*** (0.048)	-0.457*** (0.050)		-0.065 (0.054)
Any correction			-0.267*** (0.024)			-0.313*** (0.033)			-0.213*** (0.033)	
Female partner	-0.003 (0.016)	-0.001 (0.017)	0.006 (0.014)	0.008 (0.014)	-0.009 (0.021)	0.001 (0.019)	0.004 (0.019)	0.007 (0.026)	0.012 (0.021)	0.012 (0.022)
Partner's contribution			1.181*** (0.054)	1.192*** (0.058)		1.171*** (0.076)	1.164*** (0.078)		1.196*** (0.076)	1.234*** (0.084)
Individual FE		✓	✓	✓	✓	✓	✓	✓	✓	✓
P-value: Good correction =Bad correction	0.000	0.000		0.013	0.000		0.252	0.000		0.014
Baseline mean	0.780	0.780	0.780	0.780	0.780	0.780	0.780	0.778	0.778	0.778
Baseline SD	0.414	0.414	0.414	0.414	0.414	0.414	0.414	0.416	0.416	0.416
Adj. R-squared	0.104	0.100	0.309	0.314	0.111	0.320	0.330	0.090	0.300	0.300
Observations	3180	3180	3180	3180	1670	1670	1670	1510	1510	1510
Individuals	464	464	464	464	244	244	244	220	220	220

*Notes:* This table reports the same estimation results as Table 3 but with the original contribution measure specified in the pre-analysis plan, and shows that the results are robust to using the original measure. Baseline mean and standard deviation are participants' willingness to collaborate with partners who do not make any corrections. Standard errors in parentheses are clustered at the individual level. Significance levels: \* 10%, \*\* 5%, and \*\*\* 1%.



Table C2: Response to corrections of high vs. low ability people: The original contribution measure

Dependent variable:	Willing to collaborate (yes=1, no=0)					
Sample:	All		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Good correction		-0.216*** (0.033)		-0.269*** (0.044)		-0.168*** (0.047)
Bad correction		-0.178*** (0.051)		-0.291*** (0.068)		-0.055 (0.069)
Any correction	-0.224*** (0.031)		-0.284*** (0.045)		-0.167*** (0.042)	
Female partner	0.006 (0.014)	0.007 (0.014)	0.001 (0.019)	0.002 (0.018)	0.011 (0.021)	0.010 (0.021)
Partner's contribution	1.200*** (0.068)	1.196*** (0.073)	1.208*** (0.101)	1.196*** (0.101)	1.195*** (0.089)	1.222*** (0.098)
Good correction x High ability		-0.137*** (0.052)		-0.079 (0.070)		-0.192** (0.076)
Bad correction x High ability		0.049 (0.072)		0.144 (0.094)		-0.051 (0.108)
Any correction x High ability	-0.101** (0.047)		-0.060 (0.066)		-0.130** (0.065)	
Partner's contribution x High ability	-0.039 (0.112)	-0.004 (0.118)	-0.088 (0.152)	-0.070 (0.154)	0.025 (0.167)	0.064 (0.183)
Individual FE	✓	✓	✓	✓	✓	✓
Baseline mean	0.780	0.780	0.783	0.783	0.778	0.778
Baseline SD	0.414	0.414	0.413	0.413	0.416	0.416
Adj. R-squared	0.310	0.315	0.320	0.331	0.301	0.303
Observations	3180	3180	1670	1670	1510	1510
Individuals	464	464	244	244	220	220

*Notes:* This table reports the same estimation results as Table 4 but with the original contribution measure specified in the pre-analysis plan, and shows that the results are robust to using the original measure. Baseline mean and standard deviation are participants' willingness to collaborate with partners who do not make any corrections. Standard errors in parentheses are clustered at the individual level. Significance levels: \* 10%, \*\* 5%, and \*\*\* 1%.

Table C3: Response to corrections made by women vs. men: The original contribution measure

Dependent variable:	Willing to collaborate (yes=1, no=0)					
Sample:	All	Female		Male		
	(1)	(2)	(3)	(4)	(5)	(6)
Good correction		-0.268*** (0.038)		-0.338*** (0.049)		-0.180*** (0.058)
Bad correction		-0.232*** (0.054)		-0.275*** (0.069)		-0.167** (0.084)
Any correction	-0.277*** (0.034)		-0.348*** (0.049)		-0.192*** (0.048)	
Female partner	-0.053 (0.049)	-0.072 (0.052)	-0.099 (0.070)	-0.090 (0.074)	-0.011 (0.069)	-0.063 (0.072)
Partner's contribution	1.115*** (0.082)	1.109*** (0.085)	1.064*** (0.116)	1.070*** (0.114)	1.159*** (0.116)	1.147*** (0.125)
Good correction x Female partner		-0.008 (0.046)		0.063 (0.061)		-0.090 (0.071)
Bad correction x Female partner		0.143* (0.077)		0.085 (0.108)		0.188* (0.105)
Any correction x Female partner	0.023 (0.044)		0.069 (0.063)		-0.035 (0.062)	
Partner's contribution x Female partner	0.124 (0.107)	0.163 (0.113)	0.201 (0.152)	0.182 (0.159)	0.061 (0.150)	0.168 (0.157)
Individual FE	✓	✓	✓	✓	✓	✓
Baseline mean	0.780	0.780	0.783	0.783	0.778	0.778
Baseline SD	0.414	0.414	0.413	0.413	0.416	0.416
Adj. R-squared	0.309	0.314	0.321	0.331	0.299	0.301
Observations	3180	3180	1670	1670	1510	1510
Individuals	464	464	244	244	220	220

*Notes:* This table reports the same estimation results as Table 5 but with the original contribution measure specified in the pre-analysis plan, and shows that the results are robust to using the original measure. Baseline mean and standard deviation are participants' willingness to collaborate with partners who do not make any corrections. Standard errors in parentheses are clustered at the individual level. Significance levels: \* 10%, \*\* 5%, and \*\*\* 1%.

Table C4: Response to corrections made by women vs. men: Heterogeneity by gender bias, the original contribution measure

Dependent variable:	Willing to collaborate (yes=1, no=0)					
Sample:	All		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Good correction		-0.254*** (0.051)		-0.327*** (0.063)		-0.151* (0.083)
Bad correction		-0.211*** (0.067)		-0.173* (0.091)		-0.268*** (0.096)
Any correction	-0.275*** (0.045)		-0.318*** (0.059)		-0.213*** (0.072)	
Female partner	0.020 (0.061)	-0.004 (0.065)	-0.006 (0.086)	0.005 (0.092)	0.041 (0.086)	-0.029 (0.087)
Partner's contribution	1.254*** (0.097)	1.247*** (0.103)	1.246*** (0.138)	1.275*** (0.139)	1.251*** (0.137)	1.203*** (0.149)
Good correction x Female partner		-0.047 (0.066)		0.025 (0.087)		-0.159 (0.102)
Bad correction x Female partner		0.161* (0.094)		0.042 (0.130)		0.327** (0.129)
Any correction x Female partner	0.001 (0.059)		0.046 (0.080)		-0.064 (0.089)	
Partner's contribution x Female partner	-0.020 (0.130)	0.033 (0.140)	0.021 (0.186)	0.007 (0.202)	-0.047 (0.182)	0.100 (0.186)
Good correction x High bias		-0.037 (0.076)		-0.037 (0.100)		-0.054 (0.117)
Bad correction x High bias		-0.040 (0.104)		-0.188 (0.132)		0.175 (0.159)
Any correction x High bias	-0.014 (0.069)		-0.074 (0.100)		0.035 (0.098)	
Female partner x High bias	-0.166* (0.099)	-0.152 (0.104)	-0.198 (0.139)	-0.191 (0.143)	-0.135 (0.139)	-0.095 (0.145)
Partner's contribution x High bias	-0.303* (0.164)	-0.299* (0.167)	-0.382* (0.226)	-0.404* (0.217)	-0.212 (0.236)	-0.148 (0.254)
Good correction x Female partner x High bias		0.085 (0.094)		0.089 (0.125)		0.134 (0.141)
Bad correction x Female partner x High bias		-0.026 (0.151)		0.068 (0.212)		-0.225 (0.200)
Any correction x Female partner x High bias	0.053 (0.089)		0.061 (0.128)		0.067 (0.124)	
Partner's contribution x Female partner x High bias	0.322 (0.214)	0.289 (0.225)	0.382 (0.301)	0.354 (0.311)	0.272 (0.303)	0.186 (0.318)
Individual FE	✓	✓	✓	✓	✓	✓
Baseline mean	0.781	0.781	0.783	0.783	0.779	0.779
Baseline SD	0.414	0.414	0.413	0.413	0.415	0.415
Adj. R-squared	0.310	0.315	0.322	0.332	0.298	0.299
Observations	3173	3173	1670	1670	1503	1503
Individuals	463	463	244	244	219	219

Notes: his table reports the same estimation results as Table B1 but with the original contribution measure specified in the pre-analysis plan, and shows that the results are robust to using the original measure. Baseline mean and standard deviation are participants' willingness to collaborate with partners who do not make any corrections. Standard errors in parentheses are clustered at the individual level. Significance levels: \* 10%, \*\* 5%, and \*\*\* 1%.

## Appendix D Experimental instructions: English translation

**App: pt0**

**Page: Reg**

**Registration**

Please fill out the following information in order for us to pay you after the session. Please make sure that they correspond to the information you registered on ORSEE.

N.B. Please capitalize only the first letter of your first name and last name.

Good examples: Marco Rossi; Maria Bianchi; Anna Maria Gallo

Bad examples: MARCO ROSSI; maria bianchi; Anna maria Gallo

- First name: [Textbox]
- Last name: [Textbox]
- Email address registered on ORSEE: [Textbox]

[Check if there are any same first names. If so, add an integer (starting from 2) at the end of the first name]

**Page: Draw**

**Draw a coin**

Please draw a virtual coin by clicking the button below.

[Draw]

[Assign random number ranging from 1 to 40]

**Page: Wait**

**Your coin**

You drew the following coin.



Please wait until the session starts.

**Page: Excess**

**Please click an appropriate button**

[I was chosen to participate]

[I was chosen to leave]

**Page: Intro**

## General instructions

**Overview:** This study will consist of **3 parts** and a follow-up survey and is expected to take **1 hour**. At the beginning of each part, you will receive specific instructions, followed by a set of understanding questions. You must answer these understanding questions correctly to proceed.

**Your payment:** For completing this study, you are guaranteed **2€** for your participation, but can earn up to **25€** depending on how good you are at the tasks. The tasks involve solving sliding puzzles, like the one shown below.

1	2	
4	5	3
7	8	6

puzzle\_2\_0.png

**Confidentiality:** Other people participating in this study can see your first name. Aside from your first name, other participants will not see any information about you. **At the conclusion of the study, all identifying information will be removed and the data will be kept confidential.** If there is more than one participant with the same first name, we add a number at the end of your first name (e.g. Marco2).

**General rules:** During the study, please turn off your camera and microphone, and do not communicate with anyone other than us. Also, please do not reload the page or close your browser because it may make your puzzle unsolvable. If you have any questions or face any problems, please send us a private chat on Zoom.

**App: pt1**

**Page: Intro**

## Instructions for part 1 out of 3

In this part, you will solve the puzzle alone to familiarize yourself with it. You can solve as many puzzles as possible (but a maximum of 15 puzzles) in **4 minutes**. You will earn **0.2€ for each puzzle** you solve.

Your goal is to move the tiles and order them as follows:

1	2	3
4	5	6
7	8	

puzzle\_goal.png

Before you start, please go through the three examples below to understand how to solve the puzzle.

**Example 1:**

First, consider the following puzzle.

1	2	3
4	5	
7	8	6

puzzle\_1.png

You can only move the tiles next to an empty cell and the tile you choose is moved to the empty cell. So, in this puzzle, there are 3 moves you can make: move 3 down, move 5 right, and move 6 up.

Among the 3 moves, moving 6 up is the only correct move: by moving 6 up, you can solve the puzzle. The other moves do not solve the puzzle.

When you click a tile next to an empty cell, the tile will be moved to the empty cell. So, in this case, you should click 6 to move it up.

**Example 2:**

Next, consider the following puzzle.

1	2	
4	5	3
7	8	6

puzzle\_2\_0.png

First, there are 2 moves you can make: move 2 right and move 3 up. Which moves should you make?

Observe that the only tiles that are not in the correct order are 3 and 6. So, you should move 3 up.

After moving 3 up, the puzzle will look like the one in example 1. Then you should move 6 up and the puzzle will be solved.

**Example 3:**

Finally, consider the following puzzle.

1	2	3
8	7	5
4		6

puzzle\_3\_0.png

This puzzle is a bit complicated but observe that the top row is already in the correct order. So, let's keep the top row as is, and think about the remaining part. **When the top row is in the correct order, you should always keep it as is.** So, think of this puzzle as the following simpler puzzle.



8	7	5
4		6

puzzle\_3\_0\_2x3.png

You could solve the puzzle by trial and error. However, **after making the top row in the correct order, you should next make the left column in the correct order** to solve the puzzle faster. There are two moves you can make: move 4 right and move 7 down. Which is the faster way to make the left column in the correct order?

Let's try moving 4 right.

1	2	3
8	7	5
	4	6

puzzle\_3\_1\_bad\_0.png

Now the only tile you can move is 8. So, let's move it down.

1	2	3
	7	5
8	4	6

puzzle\_3\_1\_bad\_1.png

Now, if you ignore the top row which is already in the correct order, the only tile you can move is 7. So, let's move it to the left.

1	2	3
7		5
8	4	6

puzzle\_3\_1\_bad\_2.png

Then move 4 up, move 8 right, and move 7 down. Then you have made the left column in the correct order. You have moved tiles seven times until now.

1	2	3
4		5
7	8	6

puzzle\_3\_1\_bad\_3.png

Now let's also keep the left column as is.

	5
8	6

puzzle\_3\_1\_bad\_3\_2x2.png

Then you can solve the puzzle by moving 5 left and then 6 up. With this method, **you have moved tiles nine times in total.**

Let's go back to the initial puzzle.

1	2	3
8	7	5
4		6

puzzle\_3\_0.png

This time, let's try moving 7 down.

1	2	3
8		5
4	7	6

puzzle\_3\_1\_good.png

Then move 8 right, 4 up, and 7 left. Now you have made the left column in the correct order only with four moves.

1	2	3
4	8	5
7		6

puzzle\_3\_4\_good.png

Let's keep the left column as is (as well as the top row).



puzzle\_3\_4\_good\_2x2.png

Now it's easy to solve the puzzle: move 8 down, 5 left, and 6 up. With this method, **you have only moved tiles seven times in total.**

Because there is a time limit, it's better to solve the puzzle with the minimum number of moves. **We call a move a good move if it makes a puzzle closer to the solution, and a bad move if it makes a puzzle far from the solution. There are no neutral moves: all moves are either good or bad.**

**In summary: when you solve the puzzle, first make the top row in the correct order, then make the left column in the correct order. Always try to make the number of moves as small as possible.**

**Understanding questions:**

Before you proceed, please answer the following understanding questions. After you answer, please click Next.

1. Which of the following statements is true?

- ☒ In this part, I will work on the puzzles individually for 4 minutes and earn 0.2€ for each puzzle I solve.
- ☐ In this part, I will work on the puzzles in pairs for 4 minutes and earn 0.2€ for each puzzle we solve.
- ☐ In this part, I will work on the puzzles individually for 4 minutes, but I will not earn anything.

2. Which of the following puzzles is in the correct order?

- ☐ A
- ☒ B

A

1	2	
4	5	3
7	8	6

puzzle\_2\_0.png

B

1	2	3
4	5	6
7	8	

puzzle\_goal.png

3. What is the strategy you should use to solve the puzzle as fast as possible?

- First, make the left column in the correct order, then the bottom row. Always minimize the number of moves I make.
- First, make the top row in the correct order, then the right column. Always minimize the number of moves I make.
- ✓ First, make the top row in the correct order, then the left column. Always minimize the number of moves I make.

4. Look at the following puzzle. Which is the good move?

- Move 4 down.
- ✓ Move 7 left.

1	2	3
4	8	5
	7	6

puzzle\_3\_3\_good.png

5. Consider the puzzle in question 4. What is the minimum number of moves to solve the puzzle?

- 2
- 3
- ✓ 4

6. Look at the following puzzle. Which is the good move?

- ✓ Move 5 left.
- Move 8 up.

1	2	3
4		5
7	8	6

puzzle\_3\_5\_good.png

7. Consider the puzzle in question 6. What is the minimum number of moves to solve the puzzle?

- ✓ 2
- 3
- 4

Page: Ready

### Be ready

[5 seconds time count]

Please be ready for the individual round.

Page: Game

### Individual round

[4 minutes time count]

[max. 15 puzzles with increasing difficulty]

Page: Proceed

### The individual round is over

The individual round is over. You have solved **xx puzzles**.

Please click Next to proceed.

App: pt2

**Page: Intro**

### **Instructions for part 2 out of 3**

In this part, you will **choose your partner for part 3**, the next part.

Although you will not earn anything in this part, it is important to choose the best partner possible: in part 3, you will work on the puzzles for 12 minutes in a pair by moving the tiles in turn, and both you and your partner will earn 1€ for each puzzle you two solve. There is a maximum of 20 puzzles you and your partner can solve (so the maximum earning is 20€).

You will **meet 7 other people** participating in this session one by one and solve 1 puzzle together by moving tiles in turn as you would do in part 3. One of you will be randomly chosen to make the first move at the beginning of each puzzle. You will have a **2-minute limit** for each puzzle.

After solving the puzzle, you will **choose whether you want to work with this person in part 3 too**. This person or other people in this session will not see your choice. **You can choose as many people as you want.**

After you meet all the 7 people and state your choices, we will check all the choices you and the 7 other people have made, and decide each person's partner for part 3 as follows:

1. We randomly choose 1 person out of you and the other 7 people. Call this person Giovanni.
2. We then check if Giovanni has a "match": among people Giovanni has chosen, we check whether these people also have chosen Giovanni. If there is such a person, we make Giovanni and this person as partners for part 3.
3. If Giovanni has more than one match, we randomly choose one of the matches and make them as partners for part 3.
4. If Giovanni has not chosen anyone, the people Giovanni has chosen have not chosen Giovanni, or those people already have their partner, we put Giovanni on a waiting list and repeat points 1-3 above.
5. After we choose all people, we randomly match people on the waiting list as partners for part 3.

**So, even if you choose a particular person, you may not be able to work with that person in part 3.** So, choose everyone whom you want to work with in part 3.

#### **Understanding questions:**

Before you proceed, please answer the following understanding questions. After you answer, please click Next.

1. Which of the following statements is true?
  - ☒ In this part, I will choose my partner for part 3.
  - In this part, I will work on the puzzles for 12 minutes in a pair by moving the tiles in turn.

2. How many people can you choose whom you want to work with in part 3?

- 1 person.
- 2 people.
- ✓ As many people as you want.

3. Why is it important to choose the best partner for part 3?

- ✓ because how many puzzles I can solve in part 3 depends on my partner's moves.
- because my partner will solve puzzles for me.

4. Suppose you have chosen Giovanni and Valeria. However, while Valeria has chosen you, Giovanni has not. If we have randomly chosen you first, who will be your partner for part 3?

- Giovanni
- ✓ Valeria
- Someone on the waiting list
- Randomly chosen from Giovanni and Valeria

5. Suppose you have chosen Giovanni and Valeria. However, unlike question 4, while Giovanni has chosen you, Valeria has not. If we have randomly chosen you first, who will be your partner for part 3?

- ✓ Giovanni
- Valeria
- Someone on the waiting list
- Randomly chosen from Giovanni and Valeria

6. Suppose you have chosen Giovanni and Valeria. Also, both Giovanni and Valeria have chosen you. If we have randomly chosen you first, who will be your partner for part 3?

- Giovanni
- Valeria
- Someone on the waiting list
- ✓ Randomly chosen from Giovanni and Valeria

7. Suppose you have chosen Giovanni and Valeria. Also, both Giovanni and Valeria have chosen you. However, we already matched Valeria with Giovanni before we choose you. Who will be your partner for part 3?

- Giovanni
- Valeria
- ✓ Someone on the waiting list
- Randomly chosen from Giovanni and Valeria

8. Suppose you have not chosen anyone. Also, both Giovanni and Valeria have chosen you. If we have randomly chosen you first, who will be your partner for part 3?

- Giovanni
- Valeria



- ✓Someone on the waiting list
- Randomly chosen from Giovanni and Valeria

9. Suppose you have chosen Giovanni and Valeria. However, neither Giovanni nor Valeria has chosen you. If we have randomly chosen you first, who will be your partner for part 3?

- Giovanni
- Valeria
- ✓Someone on the waiting list
- Randomly chosen from Giovanni and Valeria

**Page: Puzzle**

### **Puzzle 1/2/3/4/5/6/7 out of 7**

You are playing the puzzle with [this person's ID]

[2 minutes time count]

**Page: Pref**

### **Puzzle 1/2/3/4/5/6/7 out of 7**

You have played the puzzle with [this person's ID]. Do you want to work with [this person's ID] in part 3?

[Yes, No]

**App: pt3**

**Page: Partner**

### **Your partner for part 3**

Based on your and the 7 other people's choices, [the partner's ID] became your partner for part 3.

**Page: Intro**

### **Instructions for part 3 out of 3**

In this part, you will work on the puzzles with your partner for **12 minutes** by moving the tiles in turn, and both you and your partner will earn **1€ for each puzzle** you two solve. There is a maximum of 20 puzzles you and your partner can solve (so the maximum earning is 20€). As in part 2, one of you will be randomly chosen to make the first move at the beginning of each puzzle.

**Understanding questions:**

Before you proceed, please answer the following understanding questions. After you answer, please click Next.

1. Which of the following statements is true?

- ✓ In this part, you and your partner will both earn 1€ for each puzzle you two solve, which means you will earn 1€ for each puzzle you two solve.
- In this part, you and your partner will earn 1€ for each puzzle you two solve, which means you will earn 0.5€ for each puzzle you two solve.

2. You and your partner...

- ✓ will work on the puzzles for 12 minutes by moving the tiles in turn. Which of you will make the first move is randomly determined at the beginning of each puzzle.
- will work on the puzzles for 12 minutes. Which of you will make the first move is randomly determined at the beginning of this part and fixed afterward.

**Page: Ready**

### **Be ready**

[5 seconds time count]

Please be ready for the group round.

**Page: Game**

### **Puzzle 1/2/3/.../20**

Your partner: [the partner's ID]

[12 minutes time count]

[max. 20 puzzles with increasing difficulty]

**Page: Proceed**

### **The group round is over**

The group round is over. You have solved xx puzzles.

Please click Next to proceed.

**App: pt4**

**Page: Intro**

### **A follow-up survey**

As the last task, we will ask you a series of questions in which there are no right or wrong answers. We are only interested in your personal opinions. We are interested in what

characteristics are associated with people's behaviors in this study. **The answers you provide will in no way affect your earnings in this study and are kept confidential.**

Please click Next to start the survey.

**Page: SurveyASI**

### **Survey page 1 out of 2**

Below is a series of statements concerning men and women and their relationships in contemporary society. Please indicate the degree to which you agree or disagree with each statement.

- Women are too easily offended.
- Many women are actually seeking special favors, such as hiring policies that favor them over men, under the guise of asking for "equality."
- Men should be willing to sacrifice their own wellbeing in order to provide financially for the women in their lives.
- Many women have a quality of purity that few men possess.
- No matter how accomplished he is, a man is not truly complete as a person unless he has the love of a woman.
- Women exaggerate problems they have at work.

[Choices: Strongly agree, Agree a little, Neither agree nor disagree, Disagree a little, Strongly disagree]

**Page: SurveyDem**

### **Survey page 2 out of 2**

Please tell us about yourself and your opinion about this study.

- Your age: [Integer]
- Gender: [Male, Female]
- Region of origin: [Northwest, Northeast, Center, South, Islands, Abroad]
- Field of study: [Humanities, Law, Social Sciences, Natural Sciences/Mathematics, Medicine, Engineering]
- Degree program: [Bachelor, Master/Post-bachelor, Bachelor-master combined (1st, 2nd, or 3rd year), Bachelor-master combined (4th year or beyond), Doctor]
- What do you think this study was about? [Textbox]
- Was there anything unclear or confusing about this study? [Textbox]
- Were the puzzles difficult? [Difficult, Somewhat difficult, Just right, Somewhat easy, Easy]
- Do you have any other comments? (optional) [Textbox]

**Page: ThankYou**

**Thank you for your participation**

Thank you for your participation. You have completed the study.

Your earnings:

- 2€ for your participation.
- xx.x€ for the puzzles you solved in part 1.
- xx€ for the puzzles you and your partner solved in part 3.

Thus, you have earned xx.x€ in this study. We will pay you your earnings via PayPal within 2 weeks. If you haven't received your earnings after 2 weeks, please contact us.

**Optional:** If you would like to know the results of this study, we are more than happy to send you the working paper via email once we finish this study.

[No, I do not want to receive the working paper] [Yes, I want to receive the working paper]

**App: pt99**

**Page: ThankYou**

### **Thank you for showing up**

Thank you for showing up in this study. You will receive the show up fee of 2€ via PayPal within 2 weeks. If you haven't received your earnings after 2 weeks, please contact us.