Gender Differences in the Cost of Corrections in Group Work

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Abstract

Collaboration is an integral component of workplace environments, and part of collaboration also involves correcting one's colleagues. Using a quasi-laboratory experiment, I study whether people dislike collaborating with someone who corrects them and whether men dislike women's correction more. I find that people, including those with high ability, are less willing to collaborate with someone who has corrected them, even if the correction improves group performance. In addition, I find suggestive evidence that men respond more negatively to women's efficiency-improving corrections but not to women's efficiency-deteriorating corrections. In contrast, women respond roughly equally negatively to any corrections by any gender. Women's or men's beliefs about gender differences in abilities cannot explain these differential responses. These findings suggest that a behavioral bias distorts the optimal selection of talent 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 a core element of workplace productivity, as most workplaces require group work (Jones 2021; Lazear and Shaw 2007; Wuchty, Jones, and Uzzi 2007). These interactions often involve correcting one's colleagues. For example, a worker may correct graphs with wrong numbers in the presentation slides one of their colleagues has prepared, or a seminar audience may point out an error in the identification assumption that the presenter is making. These corrections are essential for the groups to function well, but can also damage the collaborative relationship if people dislike being corrected. This potential interpersonal friction can be detrimental to group efficiency by its own merit but also through deterioration of workplace climate because workplace climate is an important determinant of productivity (Alan, Corekcioglu, and Sutter 2022; Edmans 2011; Guiso, Sapienza, and Zingales 2015). Further, women may experience stronger interpersonal friction with men because some men dislike to be led by women (Abel 2022; Chakraborty and Serra 2022; Husain, Matsa, and Miller 2021). This practice can contribute to gender gaps in labor market outcomes (Blau and Kahn 2017).

This paper studies whether people dislike collaborating with someone who corrects them and whether men dislike woman's correction more. I define collaboration as working with others toward the same goal, and correction as overriding what others do. Answering these questions using observational 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. In the experiment, participants are allocated to groups of eight people and are paired with each of the other group members sequentially, in random order, to solve a collaborative task together. Each time participants finish the task, they state whether they would like to collaborate with their current partner for the same task in the final stage of the experiment. This final stage is the main source of earnings for participants and thus provides a strong incentive for them to select as good a collaborator as possible. For the collaborative task, I use Isaksson (2018)'s number-sliding puzzle, which allows us to calculate an objective measure of each participant's contribution to the collaborative task and to classify each move as good (moving the puzzle closer to the solution) or bad (moving the puzzle further away from the solution). I define a correction as reversing a partner's move; this gives us a comparable measure across different participants and allows us to objectively classify corrections as either good or bad. Participants are informed at the beginning of the experiment of the notion of good and bad moves, how to solve the puzzles efficiently, and how the collaborator will be selected for the final stage.

I find that participants understand the notion of good and bad moves; the more a participant contribute to solving the puzzle, the more likely 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 individual contributions, participants are less willing to collaborate with someone who has corrected their moves, even if the corrections moved the puzzle closer to the solution. This is not because participants misunderstood good corrections as bad ones, as even high ability participants – those who should be better able to identify good and bad corrections – respond negatively to corrections. Thus, the negative response is likely to be irrational. Although only suggestive (at the 10% statistical significance level), I also find evidence that men respond more negatively to women's good corrections but not to women's bad corrections: men dislike women correcting their mistakes but did not dislike women making mistakes on their own. On the other hand, women respond equally negatively to both women's and men's good and bad corrections. These findings are unlikely to be due to women's or men's beliefs about the differences in women's and men's abilities in solving the puzzle: women and men contribute equally well to the puzzle, and neither women nor men under- or overestimate women's contribution. Taken together, these findings suggest that a behavioral bias distorts the optimal selection of talents and penalizes those who correct others' mistakes, and that men may exhibit stronger bias when women correct them.

Isaksson (2018) uses the same puzzle to study whether women underclaim their contribution to the group work using the novel property that enables a researcher to objectively measure one's contribution to the puzzle. While I use Isaksson's puzzle and benefit from its novel property, my research questions and experimental design are different. Specifically, I examine whether receiving corrections reduces one's willingness to collaborate with that person and whether men react more negatively to women's corrections using a design adapted from Fisman et al. (2006, 2008)'s speed dating experiments but for working partner preference instead of romantic partner preference.

This paper's contribution is twofold. First, it contributes to the literature on workplace climate and productivity by showing that interpersonal frictions can distort group efficiency, and that the frictions may have a stronger effect on women. My findings complement Alan, Corekcioglu, and Sutter (2022), who find that a better workplace climate increases worker satisfaction and the degree of mutual reciprocation, while reducing toxic competition and worker turnover. Alan et al. argue that improved manager-worker relationships are the most likely mechanism. Aside from Alan et al., my findings also relate to the organizational economics literature: the literature finds that firms with high employee satisfaction exhibit higher stock prices (Edmans 2011) and that a firm perform better when its workers perceive their managers as trustworthy and ethical (Guiso, Sapienza, and Zingales 2015). In addition, I show that the same environment can affect women and men 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 – as do men in female-dominant jobs.

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.

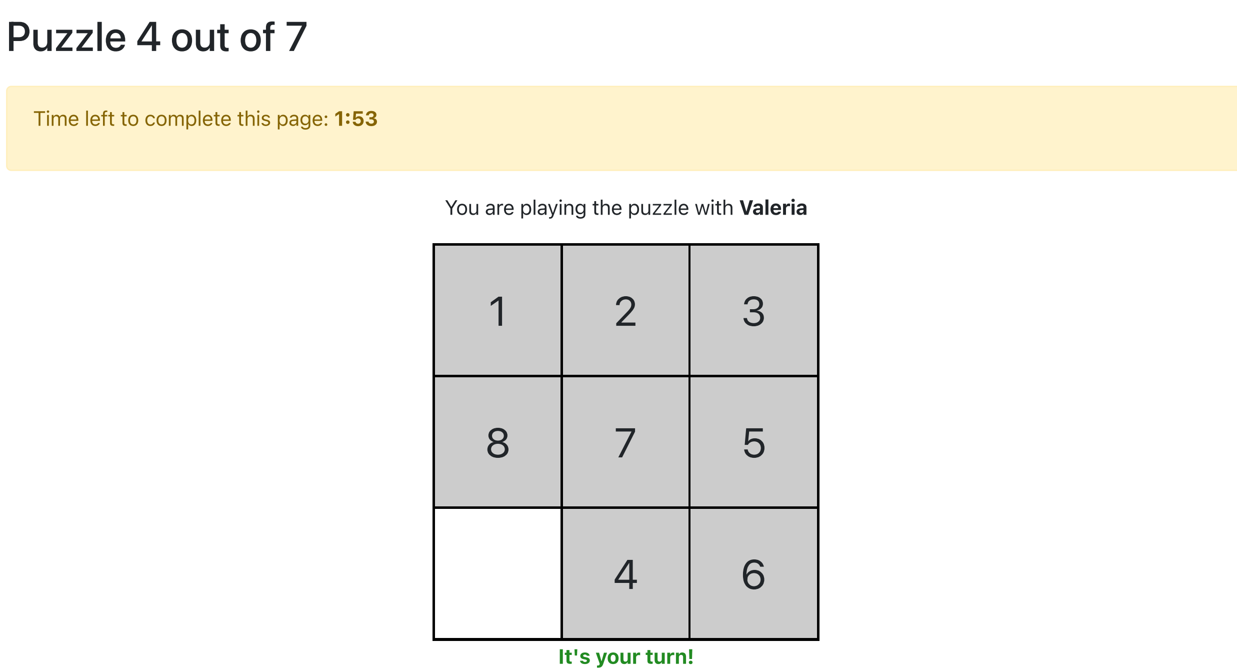
The remainder of the paper proceeds as follows. In section 2, I describe the experimental design, procedure, and implementation. Next, I describe the data obtained from the experiment in section

3. Then, I provide a simple theoretical framework to show how a rational agent would behave in section 4. Afterward, I proceed to empirical analysis: I present the empirical strategy in section 5 and present the results in 6. I show the robustness of the results in section 7. Finally, I conclude the paper in section 8.

2 Experiment

Introducing the quasi-laboratory format I run the experiment in a quasi-laboratory format where we experimenters and the participants are connected via Zoom throughout the experiment, but turn off participants' cameras and microphones except at the beginning of the experiment. Aside from that participants participate remotely using their computers, the experiment is conducted as it would be in a physical laboratory. Appendix A discusses the advantages and drawbacks of the quasi-laboratory format relative to physical laboratory and standard online experiments.

Figure 1: Puzzle screen



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

The collaborative task For 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.[1] This puzzle has nice mathematical properties: I can define the puzzle's difficulty and classify a

1. Each participant has to make a move during their turn; they cannot pass.

given move as either good or bad via the Breadth-First Search algorithm.[2] Based on the number of good and bad moves a participant makes, I can calculate individual contributions to the task: the contributions are measured 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 objectively compare the quality of corrections by different participants.[3] 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).

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.[4] Since a correction is also a move, it is also either good or bad. 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.

2.1 Design and procedure

Registration

Upon receiving an invitation email to the experiment, participants register for the session they want to participate in, and upload their ID documents as well as a signed consent form.[5]

Pre-experiment

Participants enter the Zoom waiting room on the day and at the time of the session they have registered for.[6] They receive a link to the virtual room for the experiment and enter their first name, last name, and the email address they used in the registration. They also draw a virtual coin numbered from 1 to 40 without replacement.

As participants arrive and are verified, I admit them to the Zoom meeting room one by one and rename them using the first name they have just entered. This information is necessary to match up their earnings in this experiment to 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

2. The difficulty is defined as the number of moves away from the solution; a good move is defined as a move that reduces the distance (in number of moves) to the solution, while a bad move is defined as a move that increases the distance to the solution.

3. Because some corrections happen early in the puzzle and the others later in the puzzle, Thus, what I capture in the analysis is the average effect of a correction.

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

5. I recruited a few more participants than needed for each session in case some participants did not show up to the session.

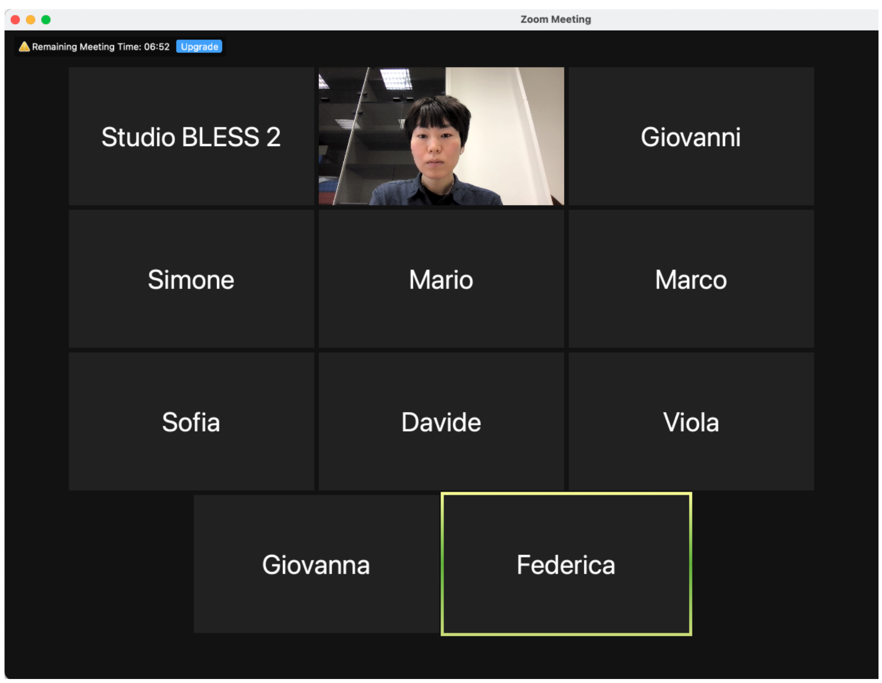
6. The Zoom link is sent with an invitation email; I checked that each participant in the waiting room indeed had registered for that session before admitting them to the main room.

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 a 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 verbally via their 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 drawn number to leave.[7] Those who leave the session receive a 2€ show-up fee. Figure 2 shows the Zoom screen participants would see during 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 giving the rules of the experiment and take questions on Zoom. Once participants start the main part of the experiment, they can only communicate with the experimenter via Zoom's private chat.

Figure 2: Zoom screen



Notes: This figure shows the 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.

7. 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 the next number until the number of participants is 16. I share my computer screen during this process so that participants see the numbers are actually drawn randomly.

Part 1: Individual practice stage

Participants first work on the puzzle individually with an incentive (0.2€ for each puzzle they solve). They can solve as many puzzles as possible in 4 minutes (maximum 15 puzzles) with increasing difficulty. After the 4 minutes are up, 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 based on how many puzzles they solve.

At the beginning of part 1, I explain participants in depth how to solve the puzzle efficiently (in minimum moves) and provide comprehension questions about the solution strategies; see the instructions in Appendix D.[8]

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 divided into a group of 8, with participants of similar ability measured in part 1 placed in the same group. 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 they 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 – that is, correct – their partner's move.[9] Each participant's contribution to a given puzzle is measured by net good moves. Figure 1 shows a sample puzzle screen where one participant is paired with another participant called Valeria and is making their move. Each partner's first name is displayed on the computer screen throughout the puzzle, and when participants select their collaborator, to subtly inform the partner'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 (so each participant solves the puzzle with seven different partners). In each round, participants solve another puzzle in pairs, 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 all seven rounds. I set the minimum number of moves to solve the puzzles to be 8 based on a pilot so that the puzzles are neither too easy nor difficult to solve.

At the end of part 2, participants are paired according to the following algorithm:

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

9. Solving the puzzle itself is not incentivized, so participants who do not want to collaborate with a given partner or fear to receive a bad response may not reverse that partner's move, even if they think the move is wrong. However, since I am interested in the effect of correction on collaborator selection, participants' *intentions* to correct that do not end up as an actual correction do not confound the analysis.

1. For every participant 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 participants that have already 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.

At the beginning of part 2, I explain in depth this pairing algorithm along with comprehension questions so that the collaborator preference statement is incentivized.

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, which is informed to both participants as in part 2. They can solve as many puzzles as possible (maximum 20), with increasing difficulty.

Post-experiment

Each participant answers a short questionnaire, which consists of (i) the six hostile and benevolent sexism questions used by Stoddard, Karpowitz, and Preece (2020) with US college students and (ii) their basic demographic information and their impressions about the experiment.[10] The answer to their demographic information is used to know participants' characteristics as well as casually check whether they have anticipated that the experiment was about gender, for which I did not find any evidence.

After participants answer all the questions, I tell them their earnings and let them leave the virtual room and close Zoom. They later 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), all registered in 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).[11] The first two conditions were to reduce noise coming from

10. I initially planned to use a gender bias measure, constructed from the hostile and benevolent sexism questions, to test whether those with higher gender bias responded more negatively to women's corrections. However, 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.

11. The laboratory prohibits deception, so no participant had participated in an experiment with deception.

differences in socio-demographic backgrounds and race or/and ethnicity that may be inferred from participants' first names or/and voices, and the last condition was to reduce experimenter demand effects.[12] The number of participants was determined by a power simulation in the pre-analysis plan to achieve 80% power.[13] The experiment was pre-registered with the OSF.[14]

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€, 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 while 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).[15] 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.[16]

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.

12. Despite only recruiting Italy-born people, 1 male participant answered in the post-questionnaire that he was from abroad. I included this participant in the analysis anyway but the results are robust to excluding him.

13. 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.

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

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

16. No economics PhD students participated in the experiment.

3 Data description

I use part 2 data in the analysis, as that is where we can observe collaborator selection decisions. I aggregate the move-level data for each puzzle so that we can associate behaviors with 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), probability that a correction is happening in a given move (Panel B), and empirical CDF of total moves (Panel C) for female-only pairs (blue), male-only pairs (green), and mixed-gender pairs (red). Panel A shows no statistically significant differences in move quality by one's own gender or the gender of one's partner. Panel B shows that corrections happen across the moves, but there are no systematic differences in the probability that correction is happening by one's own gender or the gender of one's partner. Panel C shows that about 70% of the puzzles are solved within a minimum number of moves (the minimum number of moves is 8) and shows that one's own gender or the gender of one's partner does not matter in how fast participants solve the puzzle.

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: for both the contributions in part 2 and the number of puzzles solved in part 1, the difference between female and male participants is statistically insignificant at 5% and quantitatively insignificant.[17,18] 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 differences I find are unlikely to come from the ability differences between female and male participants. Panel A also shows that there are no gender differences in propensity to correct partners, unlike Isaksson (2018), who finds that men correct their partners more often than women, although that result is from move-level data. Finally, the last row of Panel A shows that male participants are slightly more likely to have female partners, although only three percentage points more.

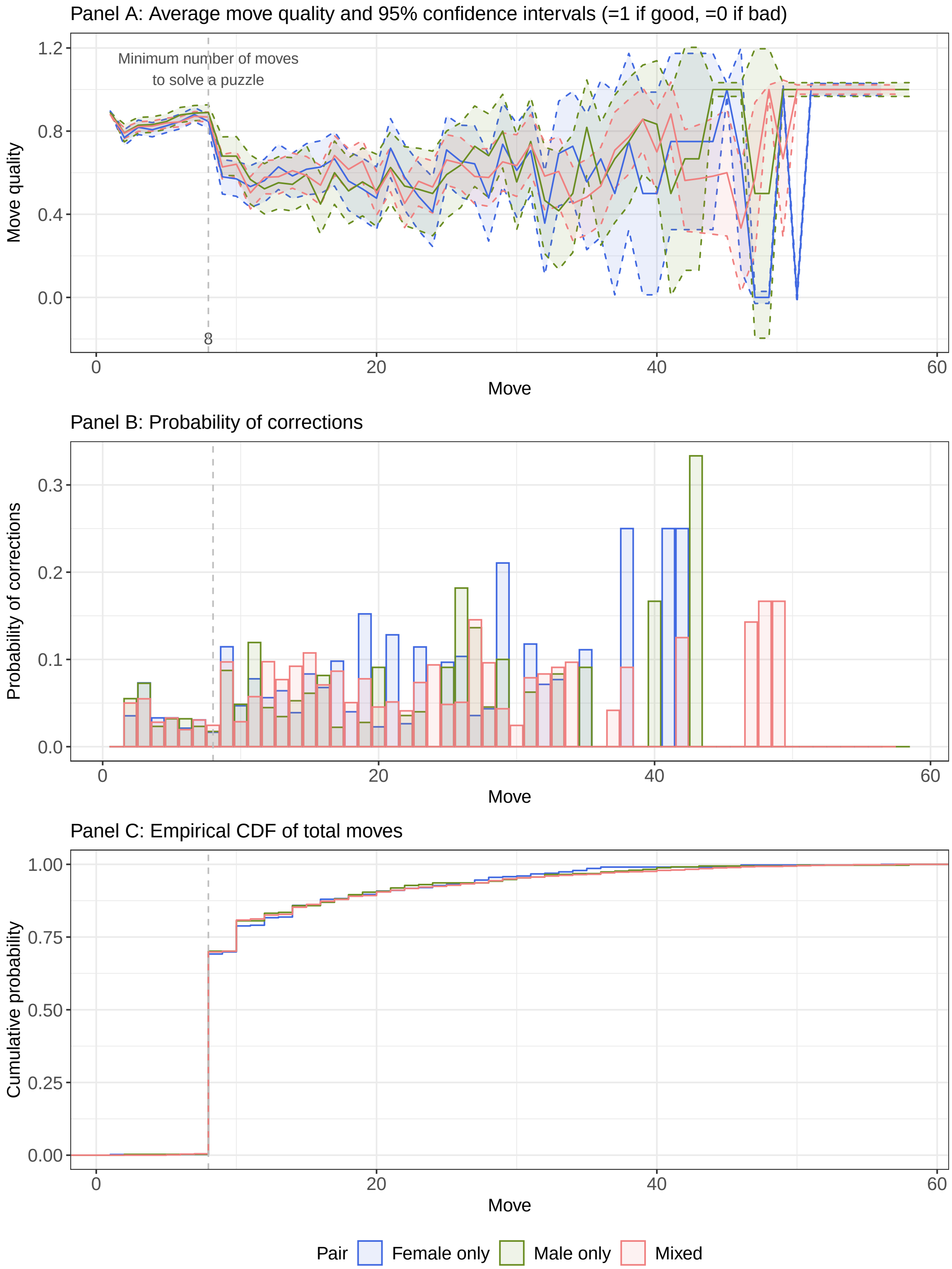
To further elaborate on panel A of Table 2, Panel A of Figure 4 presents the distribution of contribution by participants' gender, showing women and men are equally good at puzzle-solving: in about 70% of the puzzles, each participant's contribution is 4 (total good moves minus total bad moves), and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

Panel B shows that the puzzle-solving ability, as well as the propensity to correct partners' moves (both mistakes and right moves) was the same for partners paired with female and male participants, suggesting that the random pairing was successful and that any gender differences

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

18. 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 the individual level).

Figure 3: Move quality, probability of corrections, and empirical CDF of total moves



Notes: The average move quality along with 95% confidence intervals (panel A), the probability of corrections in each move (panel B), and the empirical CDF of total moves (panel C) separately for females only (blue), males only (green), and mixed gender pairs (red). The confidence interval of panel A is 95% confidence intervals of βs 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 on the tth move is good and 0 if bad. I add an estimate of β_1 to estimates of β_2-β_{58} to make the figure easier to look at. Standard errors are clustered at the pair 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
Panel A: Own behaviors							
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
Panel B: Partner's behaviors							
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
Panel C: Puzzle outcomes							
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).

I would find are not coming from partners of either gender correct more often. Participants are corrected by their partners 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 the propensity to be corrected.[19]

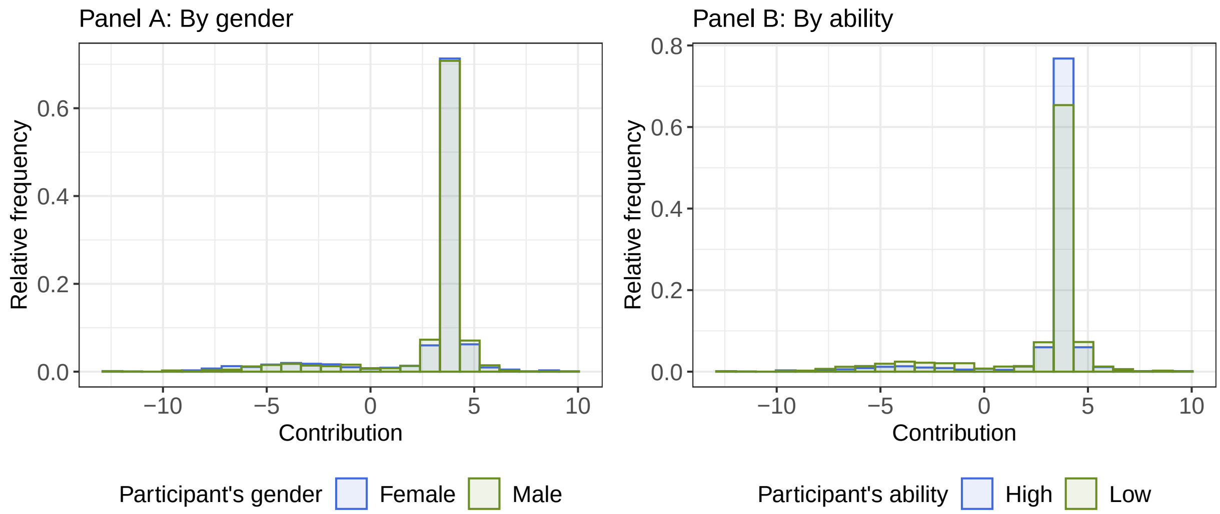
Panel C shows that participants state they want to collaborate with the paired partner 71-72% of the time. Participants spend on average 43-44 seconds for each puzzle (the maximum time a pair can spend is 120 seconds) and take 11 moves. 85-86% of the puzzles are solved, and participants correct their partner's moves consecutively in 4% of the puzzles.[20] There is no gender difference in any of these outcomes, suggesting any gender differences cannot be attributed to the imbalance in these outcomes.[21]

19. The percentage of good corrections and bad corrections do not sum up to the percentage of all corrections because 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.

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

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

Figure 4: Distribution of contributions



Notes: This figure shows the distribution of individual contributions 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 contributions, and panel B further shows that among high-ability participants, a higher fraction contributes to the puzzles 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).

3.3 Across-round balance

Figure 5 plots the 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).

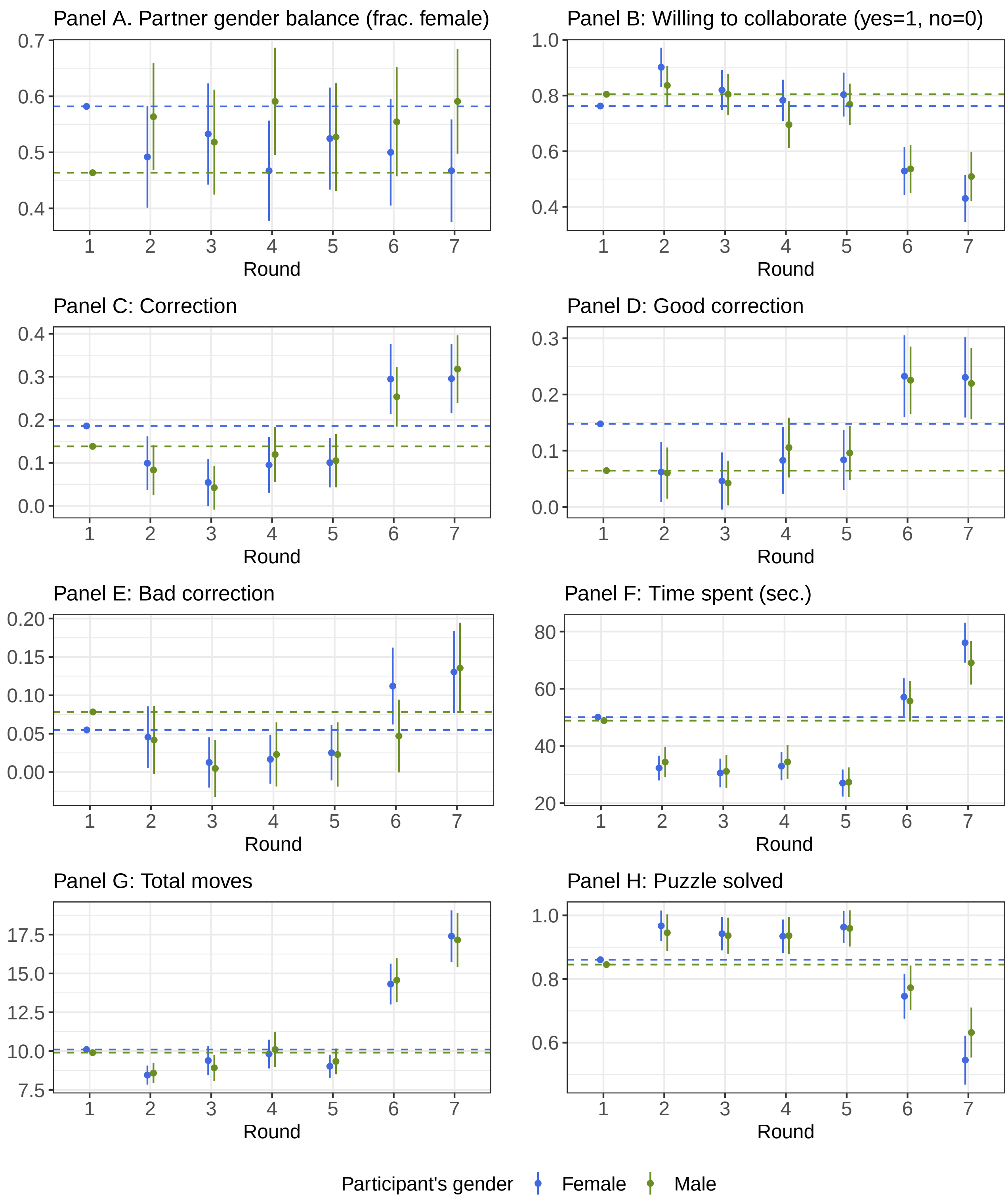
First, there is some unbalance in partner's gender across rounds between female and male participants (Panel A), with female (male) participants more (less) likely to be paired with a female partner in round 1, but the difference is not statistically significant for rounds 2-7.

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 these 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.

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 βs 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 β_1 to estimates of β_2-β_7 to make the figure easier to look at. Standard errors are clustered at the individual level.

4 Theoretical framework

In this section, 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 about 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 being willing to collaborate with j as 0 for each round t.

The payoff is increasing with 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 with j's ability as perceived by i.

Thus, i would face the following problem:

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

where each term is defined as follows:

- *Accept*: whether i is willing to collaborate with j (=0 if no, =1 if yes)
- μ_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)
- θ: i's belief about their ability relative to other participants in the session (>0 if higher, =0 if same, <0 if lower)
- ω: 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 θ and ω 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 are 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 corrections and gender convey information about j's ability, even if i is fully rational.[22]

First, keeping j's ability as perceived by i fixed, the information j's correction conveys depends on θ. 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

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

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 θ. 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:*

$$\partial\mu_j/\partial c_j^b < \partial\mu_j/\partial c_j^g \; \forall\theta \tag{2}$$

Also, the more the i understands the puzzle, the more they can observe j's move quality, and hence corrections, regardless of θ. 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 is 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 of their belief about their own ability. That is:*

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

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

Proposition 3. *A rational agent i's willingness to collaborate with j when j is a woman and made a correction, relative to when j is a man and make a correction, depends on i's 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:*

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

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

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

I consider deviations from these propositions as 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 farther away from the solution, 0 otherwise.
- $Female_j \in \{0,1\}$: an indicator variable equals 1 if j is female, 0 otherwise.
- $Contribution_j \in \mathbb{Z}$: js contribution to a puzzle played with i.
- ϵ_{ij}: omitted factors that affect i's likelihood to select j as their collaborator.

and $\mu_i \equiv \sum_{k=1}^{N} \mu^k \mathbb{1}[i = k]$ are the 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.[23]

More specifically, given 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 the paired participant's ability can affect the participant's willingness to collaborate; (ii) the participant's personality – for example, overconfidence – affects their puzzle behavior, which in turn affects the paired participant's behavior. To address the former point, I assume that $Contribution_j$ fully captures j's ability as perceived by i through j's puzzle moves (not true ability). This assumption is reasonable if we think participants' willingness to collaborate increases with the partners' contributions to the puzzle, which is consistent with the fact that participants can partially observe their partners' ability. To address the latter point, I add individual fixed effects: because j's unobservables are exogenous to i's unobservables and all i can observe about j is j's gender and puzzle behavior (correction and contribution), conditional on these observables about j, whether i selects j as their collaborator is an outcome of a particular paring which is random.

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 contributions; if i can fully observe j's ability, good and bad corrections convey no information that a rational agent cares about.

23. 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.

5.2 Heterogeneity by participants' ability

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

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

where each variable is defined as follows:

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

Other variables are as defined in equation 6.

5.3 Heterogeneity by partners' gender

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

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

Where each variable is defined as in equation 6.

6 Results

6.1 Response to corrections

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 while column 2 excludes the partner's contribution. Column 3 combines good and bad corrections 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 percentage points 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 0.271 more negative than the coefficient estimates on good corrections (p-value < 0.01).

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)
Good correction	-0.208***	-0.238***		-0.204***		-0.229***		-0.168***
	(0.028)	(0.030)		(0.024)		(0.033)		(0.036)
Bad correction	-0.518***	-0.508***		-0.100***		-0.172***		-0.011
	(0.031)	(0.034)		(0.036)		(0.047)		(0.052)
Any correction			-0.198***		-0.237***		-0.152***	
			(0.022)		(0.030)		(0.031)	
Female partner	-0.003	-0.001	0.008	0.009	0.002	0.004	0.016	0.016
	(0.016)	(0.017)	(0.014)	(0.014)	(0.018)	(0.018)	(0.021)	(0.021)
Partner's contribution			0.083***	0.084***	0.090***	0.089***	0.077***	0.080***
			(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Individual FE		✓	✓	✓	✓	✓	✓	✓
P-value: Good correction =Bad correction	0.000	0.000		0.020		0.347		0.016
Baseline mean	0.780	0.780	0.780	0.780	0.783	0.783	0.778	0.778
Baseline SD	0.414	0.414	0.414	0.414	0.413	0.413	0.416	0.416
Adj. R-squared	0.104	0.100	0.334	0.335	0.365	0.369	0.306	0.306
Observations	3180	3180	3180	3180	1670	1670	1510	1510
Individuals	464	464	464	464	244	244	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 excludes the partner's contribution. Column 3 combines good and bad corrections as a single dummy variable. Columns 5-6 present the corresponding results for women and columns 7-8 for men. The p-values (F-test) for the differences of the coefficient across columns: 0.333 for any correction in column 5 and column 7, 0.178 for good correction in column 6 and column 8, and 0.184 for bad correction in column 6 and column 8. 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%.

Corroborating this, as column 3 shows, the coefficient estimate on the partner's contribution, 0.083, is positive and both quantitatively and statistically highly significant (p-value < 0.01). This suggests that participants are 8.3 percentage points more willing to collaborate with partners who make one more good move. This is true both for women (column 5, 0.090 with p-value < 0.01) and men (column 7, 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, -0.198, is negative and both quantitatively and statistically highly significant (p-value < 0.01). This suggests that participants are 19.8 percentage points less willing to collaborate with those who made one or more corrections. To offset this effect, a partner's contribution has to increase by 0.79 standard deviations.[24] The corresponding coefficient estimates for women are -0.237 (column 5, p-value < 0.01) and -0.152 for men (column 7, p-value < 0.01). Thus, participants are less willing to collaborate with a person who corrected their

24. 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 and 2.87 for partners faced by men: (2.73+2.87)/2=2.80.

move.

This negative response to a correction 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 estimates for women are -0.229 (column 6, p-value < 0.01) and -0.168 for men (column 8, p-value $<$ 0.01).

The coefficient estimate on bad correction in column 4, -0.100, is also negative and both quantitatively and statistically significant (p-value < 0.01). However, the magnitude is smaller than the coefficient estimate on good correction, with a difference of -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 only -0.011 (column 8, 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, responses to corrections depend on participant's belief about their own ability relative to their partners. People are in general overconfident, albeit that men are more overconfident (Croson and Gneezy 2009). Thus, these behaviors may not be irrational.

6.2 Heterogeneity by participants' ability

Table 4 shows that 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 in Table 3, columns 1-2 include all participants' willingness to collaborate. Columns 3-4 show 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 it is more negative for men (column 5, p-value < 0.05). Thus, high-ability participants, in particular men, dislike receiving corrections more than low-ability participants.

It is not efficiency deteriorating or irrational 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, but it is more negative and statistically significant (p-value < 0.05) for men (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

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***		-0.208***		-0.107***
		(0.030)		(0.042)		(0.041)
Bad correction		-0.100**		-0.201***		0.005
		(0.047)		(0.064)		(0.063)
Any correction	-0.153***		-0.213***		-0.096**	
	(0.028)		(0.041)		(0.037)	
Female partner	0.008	0.009	0.002	0.002	0.015	0.014
	(0.014)	(0.014)	(0.018)	(0.018)	(0.021)	(0.021)
Partner's contribution	0.084***	0.084***	0.090***	0.089***	0.079***	0.082***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Good correction x High ability		-0.118**		-0.048		-0.180**
		(0.050)		(0.066)		(0.075)
Bad correction x High ability		0.000		0.074		-0.061
		(0.072)		(0.095)		(0.109)
Any correction x High ability	-0.108**		-0.051		-0.152**	
	(0.044)		(0.061)		(0.064)	
Partner's contribution x High ability	-0.002	-0.001	-0.002	-0.001	-0.004	-0.003
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(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. The p-values (F-test) for the differences of the coefficient across columns: 0.810 for any correction in column 3 and column 5, 0.944 for good correction in column 4 and column 6, 0.137 for bad correction in column 4 and column 6, 0.073 for any correction times high ability in column 3 and column 5, 0.057 for good correction times high ability in column 4 and column 6, and 0.409 for bad correction times high ability in column 4 and column 6. 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%.

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.

Aside from these main results, comparing the coefficient estimates on any correction in columns 3 and 5, high ability male participants dislike receiving corrections more than high ability female participants, although statistically significant only at 10% level. This effect mainly comes from good correction, as we can see from comparing the coefficient estimates on any correction in columns 4 and 6. This gender difference could be due to that men are more overconfident than women.

6.3 Heterogeneity by partners' gender

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***		-0.248***		-0.104*
		(0.035)		(0.045)		(0.053)
Bad correction		-0.176***		-0.218***		-0.104
		(0.051)		(0.064)		(0.076)
Any correction	-0.203***		-0.260***		-0.125***	
	(0.031)		(0.042)		(0.045)	
Female partner	0.013	0.001	-0.001	-0.002	0.026	0.003
	(0.022)	(0.022)	(0.032)	(0.032)	(0.029)	(0.030)
Partner's contribution	0.084***	0.083***	0.090***	0.089***	0.078***	0.077***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)
Good correction x Female partner		-0.035		0.035		-0.119*
		(0.044)		(0.057)		(0.067)
Bad correction x Female partner		0.144**		0.090		0.168
		(0.070)		(0.093)		(0.102)
Any correction x Female partner	0.009		0.047		-0.051	
	(0.041)		(0.056)		(0.059)	
Partner's contribution x Female partner	-0.002	0.002	-0.001	-0.001	-0.001	0.006
	(0.005)	(0.005)	(0.008)	(0.008)	(0.007)	(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. The p-values (F-test) for the differences of the coefficient across columns: 0.924 for any correction in column 3 and column 5, 0.732 for good correction in column 4 and column 6, 0.947 for bad correction in column 4 and column 6, 0.253 for any correction times female partner in column 3 and column 5, 0.061 for good correction times female partner in column 4 and column 6, and 0.274 for bad correction times female partner in column 4 and column 6. 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 5 presents the regression results of equation 8. As in 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 results suggest that participants – both women and men – do not underestimate women's contributions when selecting a collaborator. In other words, they correctly believe that women and men are equally good at solving the 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: as shown in 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 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 – or be led by women – but they are okay with that women make mistakes. As referred to in the introduction, several studies document men's aversion to being led by women (Abel 2022; Chakraborty and Serra 2022; Husain, Matsa, and Miller 2021).

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 the 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, these 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 their partners.

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 interactions 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.

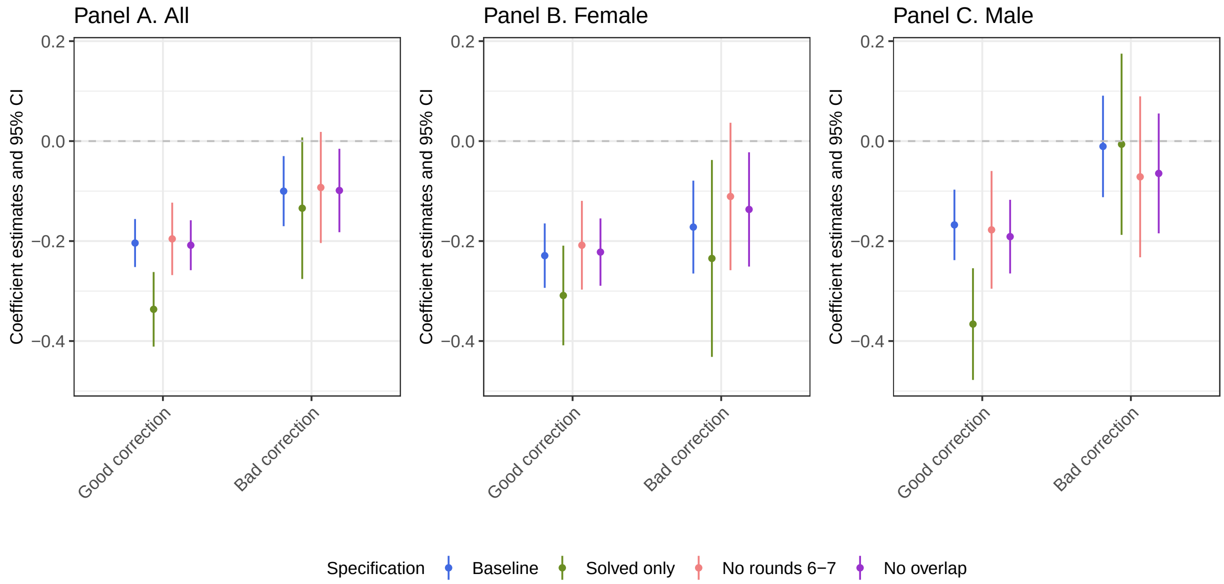
The main coefficients of interest for equation 8 are the interactions between good correction and female partner and between bad correction and female partner. Looking at Figure 8, we again see most of the coefficient estimates are close to the main estimates. The estimates with solved puzzles only present 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 the evidence that men react more negatively to women's good corrections.

8 Conclusion

This paper demonstrates that people, including those with high ability, are less willing to collaborate with someone who has corrected them, even if the correction improved group performance. I also provide suggestive evidence that men respond more negatively to women's corrections that improve group performance but not to women's corrections that deteriorate group performance, presumably because men do not like women to correct their mistakes. On the contrary, women respond roughly the same to women's and men's corrections. 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

Figure 6: Response to corrections: Robustness



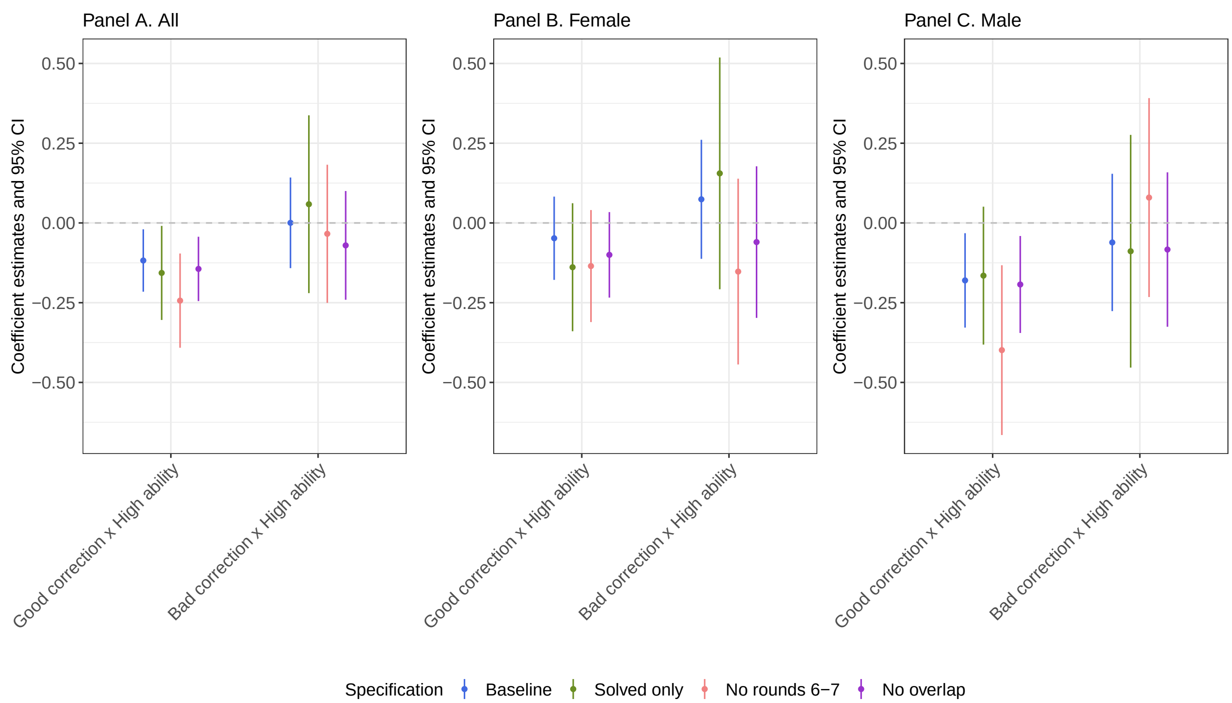
Notes: This figure plots the coefficient estimates and 95% confidence intervals of columns 4, 7, and 10 of Table 3 with solved puzzles only (the green dots and lines), with rounds 1-5 only (the red dots and lines), and with puzzles where only good or bad corrections occurred (the purple dots and lines).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

much smaller in my experiment: the puzzle-solving ability is not informative of an ability relevant for the participants' work or study – it is not something they 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 costs, using tasks that are more related to one's real-world ability, and having variation in seniority would be interesting extensions of this paper.

However, my experiment has 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 interactions would mitigate people's negative response to corrections, though 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 than the general working population, due to their age and that they are presumably more aware of that gender bias is a bad thing. 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 the study's external validity: women's corrections may receive stronger and more robust negative reactions in real workplace environments where people are older and possibly less educated.

Finally, my experiment is not designed to investigate the underlying mechanism, but the results are consistent with self-image concerns and information avoidance (Golman, Hagmann, and

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



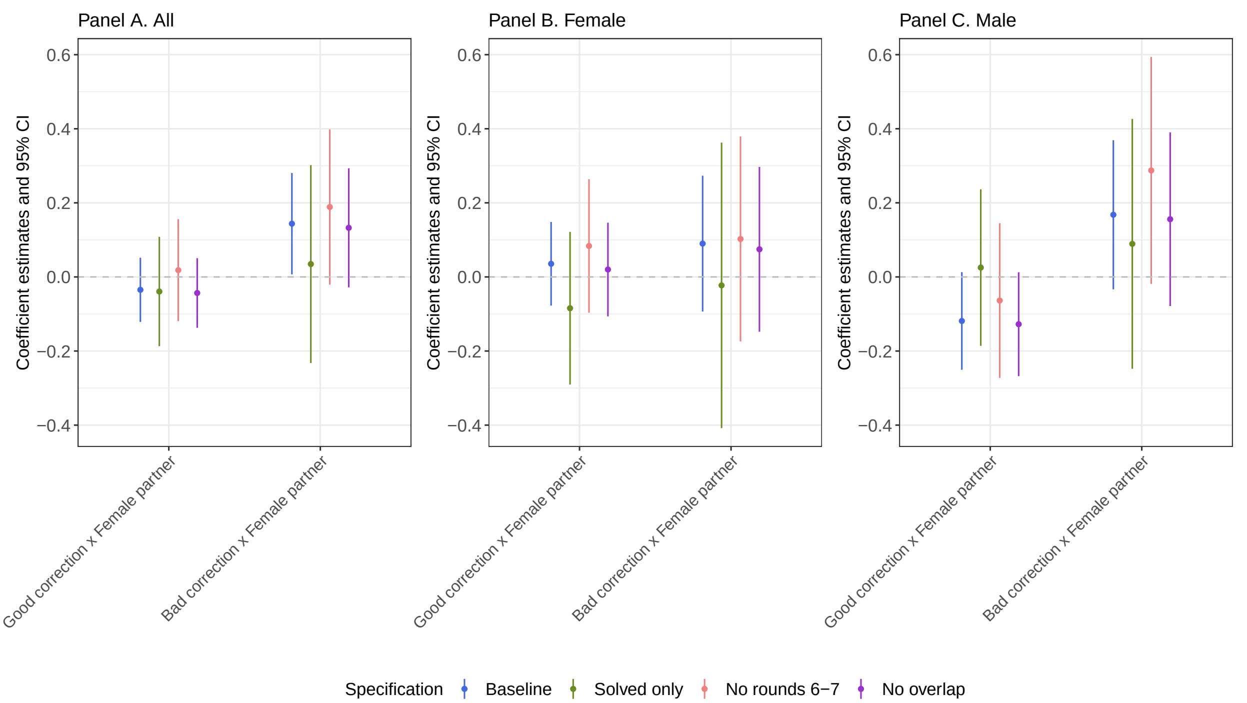
Notes: This figure plots the coefficient estimates and 95% confidence intervals of columns 2, 4, and 6 of Table 4 with solved puzzles only (the green dots and lines), with rounds 1-5 only (the red dots and lines), and with puzzles where only good or bad corrections occurred (the purple dots and lines).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

Loewenstein 2017).[25] 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 that is 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). A possible interpretation of my results is that receiving good corrections is a negative feedback, and accepting them damages people's self-image.[26]

25. Abelson (1986) is probably the first to propose this idea, who argues that people's "beliefs are like possessions" (p. 223).

26. This means θ 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 the samples in these ways.

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