The glass ceiling in experimental markets

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ABSTRACT

We study an experimental market where, in spite of equal performance across genders, individuals discriminate towards women in hiring decisions. We show that discrimination is neither taste-based nor based on a correct statistical inference regarding differences in performance. Instead, it is rooted in biased beliefs about women's abilities. The gender gap increases when candidates are allowed to influence expectations by declaring their expected performance and it narrows if individuals receive accurate information of the performance of the applicants. However, even when accurate information is transmitted, the gender gap persists because individuals do not completely update their initially biased belief. Furthermore, we show, by using the Implicit Association Test, that unconscious stereotypes are partly responsible for the initial bias in beliefs and the subsequent lack of updating.

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1. Introduction

There are large differences not only in the relative compensation, but also in the relative presence of women versus men in the highest paid jobs (e.g., Azmat, Güell, and Manning, 2004; Arulampalam, Booth, and Bryan, 2007). This underrepresentation is especially severe at the highest levels of the corporate ladder: for example, Bertrand and Hallock (2001) show that only about 2.5 percent of the five-highest paid executives in S&P 500 firms are women and Wolfers (2006) documents that over the period 1992-2004, the CEO of an S&P 1500 firm was a woman only 1.3% of the time. Moreover, the gap persists despite the narrowing gender gap in (business) education and evidence that there is no link between firm performance and the gender of top executives (Albanesi and Olivetti, 2008).

The relative differences in compensation and presence of women can be due to several reasons both form the supply side and the demand side of the labor market. On the supply side, women might be less interested in top positions because they do not like those types of jobs. The experiment of Niederle and Versterlund (2007) suggests that women like competitive environments less than men.[1] Another reason is that women may be less willing to aggressively negotiate for pay and promotion (Babcock and Laschever, 2003).

On the demand side, women may be experiencing some form of discrimination. Discrimination can be taste-based—for example, men prefer to work with other men as opposed to women (Becker, 1971)—or expectation-based (Phelps, 1972; Arrow, 1973). From a policy perspective, it makes a big difference whether expectation-based discrimination arises from an unbiased statistical inference regarding differences in performance (on average women run slower than men) or from a biased perception of women's abilities (women are believed to be worse drivers than men even though there is no statistical evidence supporting this belief).[2] In this paper, we study whether biased perceptions alone can be responsible for discrimination toward women and what mechanisms exacerbate or mitigate such phenomenon.

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[1] Some of the other papers supporting this literature are Gneezy, Niederle, and Rustichini (2003), Gneezy and Rustichini (2004), Günther et al. (2008), Dreber, von Essen, Ranehill (2009), and Gneezy, Leonard, and List (forthcoming). For a survey see Booth (2009).

[2] In addition, as argued by Arrow (1973) and Lundberg and Startz (1983), even if there are no differences in innate abilities, biased beliefs can lead to real differences in performance because they cause underinvesti01 T4o3(i01 s)-1(i)3(nhr)3(g)-1((r)3(ma(y)1(p)-1(

The effects of discrimination on market outcomes are very difficult to disentangle when relying on naturally occurring data. Even if one could perfectly control for differences in ability (which we generally cannot), it is very difficult to separate between preferences on the supply side (i.e., women 2 less likely to find any evidence in favor of it. Thus if such evidence does occur, we can be sure that it comes from biased performance expectations.

An important part of our experimental design is that we elicit directly x(t)2(ly)TJ0.003 Tc 016.383Tw 3.

The rest of the subjects in the session make six decisions, which are divided into three information conditions or treatments (two decisions per treatment). The first decision of each treatment

As a final step in our study, we asked all subjects to return to the lab two months after the experiment to complete an Implicit Association Test (IAT) between gender and scientific abilities (Greenwald, McGhee, and both genders (p = 0.018 for men, p = 0.018 for women), we do not find a significant difference between the men's improvement and the women's improvement (MW test, p = 0.489).[11]

The subjects' relative performance in the adding task in part 1 is highly predictive of their performance in the contest. For example, the Spearman's rank correlation coefficient between the two is ρ = 0.81 (p < 0.001). Consequently, the relative performance of candidates in part 1 is an excellent predictor of who wins the contest: it predicts the winner of contest 92% of the time.[12] Moreover, this predictive power is equally strong for men and women (for men it predicts the winner 94% of the time and for women 90%). Given this high predictive power, we use the candidates' past performance to determine who the ideal candidate to choose is.

3.2 Initial choices and beliefs

To analyze the subjects' beliefs and choices, we take sessions to be independent observations and make within-session comparisons of session means. Moreover, we re(na)Tw 3(n)-1(n)3( )TJ 0.002 Tc 0.002 Tw (th)-7(e)-1( )TJ one-sided tests for expected to perform better (or are chosen more often) than women.[13]

As seen in Table 1A, when subjects have no information other than the physical appearance of the two candidates, they choose a female candidate only 34% of the time. This is significantly less often than 50%, which is what one would expect if subjects randomize between choosing a man and a woman (WSR test, = 0.005). In comparison, if subjects knew the past performance of candidates and based their choice solely on this information, they would choose women 47% of the time (see Table 1B).[14]

bias in favor of men produces a gender gap in the expected earnings of candidates: women’s expected earnings are 19% lower than men’s. Note that the propensity to choose men more often is present for both genders and is even slightly stronger for female subjects than it is for males (females choose women only 33% of the time while males choose women 39% of the time).

The subjects’ choices are in line with their expectations. A look at T-6(c) Tw(n)TJse2(B)TJ Tc 0 Tw 3.219

subjects expect men to outperform women by 0.97 sums while male subjects expect men to outperform women by 0.73 sums. Moreover, the subjects' mean difference between the expected performance of women and the expected performance of

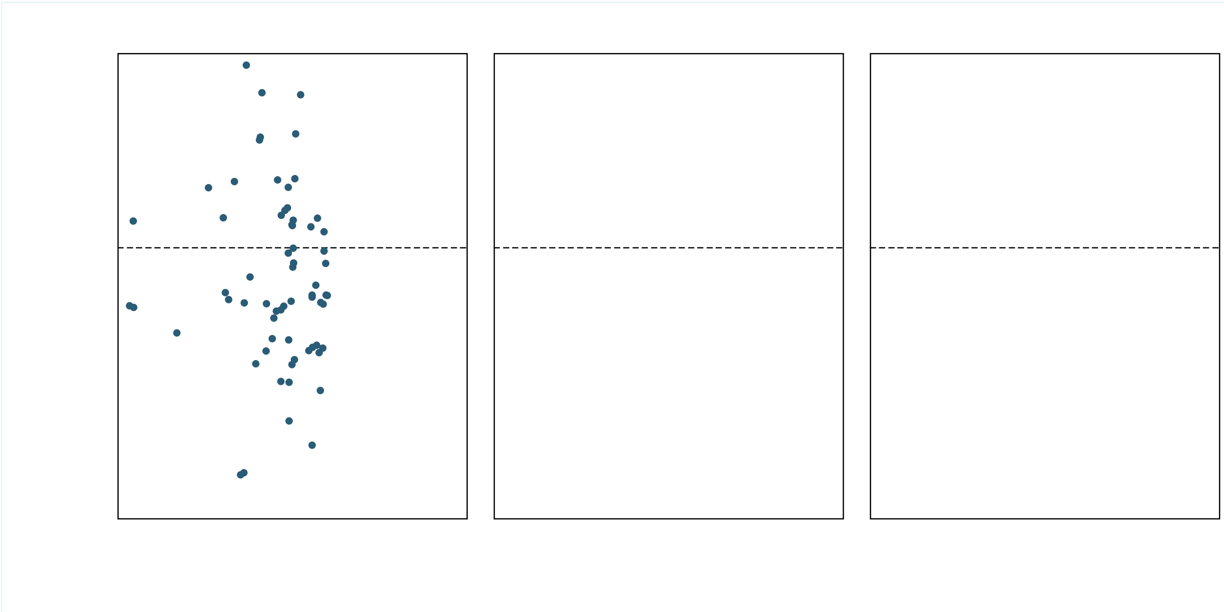

Figure 1 – IAT score and beliefs of the relative performance of men and women

Note: The lines are calculated from a regression with the difference between the expected performance of women and the expected performance of men as the dependent variable. The independent variables are the IAT score, gender, and interaction terms. OLS estimates with subject random effects and session fixed effects (see Appendix B).

individuals (i.e., with an IAT score of zero) is predicted to not be significantly different from zero (Wald test, p = 0.692).

3.3 Successive choices and updated beliefs

In real life people do not rely only on their priors but try to integrate them with extra information. We study the effect of additional information with our two other treatments.

We start with the cheap talk treatment. In spite of being highly correlated with their actual performance in the part 1 (Spearman's ρ = 0.59, p < 0.001), revealing the candidates' self-reported claims results in less women being chosen. As seen in Table 1A, women are now chosen only 27% of the time, which is significantly less than the 34% in the no-information treatment (WSR test, p = 0.017). This deterioration seems to be due to subjects treating the claims of men and women similarly, which ignores two facts. First, the claims of female candidates are significantly lower than those of male candidates (12.33 sums versus 14.82 sums; MW test, p = 0.028). Second, women's claims are more informative than those of men's. The Spearman's rank correlation coefficients between claims and actual performance are ρ = 0.66 for women and ρ = 0.56 for men.

In the past-information treatment, even with precise information of the candidates' relative performance, women candidates are chosen only 39% of the time (see Table 1A). This is significantly less than the 47% of women that would be chosen if subjects base their decision solely on the candidates' past performance (WSR test, $p = 0.038$).[18] Hence, we find a persistent bias against choosing women even after subjects have the opportunity to update their initial beliefs.

Next we take a closer look at how subjects update their beliefs concerning the relative performance of women. In particular, we use the IAT score to analyze whether the updating of beliefs is affected by implicit prejudices against women. To have a measure of the degree to which subjects update their expectations we calculate the following variable:

$$\varphi_{ik} = (\sigma_{ik} - \mu_i)/(s_{ik} - \mu_i)$$

where μ_i is subject *i*'s expected difference in performance between a woman and a man in the no-information treatment (i.e., *i*'s prior belief), s_{ik} is the information observed by *i* in treatment *k* concerning the difference in performance (i.e., either the difference in claimed performance or the difference in past performance), and σ_{ik} is *i*'s expected difference in performance after observing s_{ik} (i.e., *i*'s posterior belief). Note that, on the one hand, if φ_{ik} equals one, it indicates that *i*'s updated belief equals the information observed in treatment *k*, which is consistent with *i* treating his prior belief as being completely uninformative. On the other hand, if φ_{ik} equals zero, it indicates that *i* did not update his belief at all, which is consistent with *i* treating the observed information in treatment *k* as completely uninformative. The mean value of φ_{ik} is 0.60 in the cheap talk treatment and 0.77 in the past performance treatment.[19] We provide the complete distribution of φ_{ik} in Appendix B.

To evaluate the effect of the IAT score on the updating process we ran a regression with φ_{ik} as the dependent variable. As independent variables we use: a dummy variable indicating who the better-performing candidate is according to the new information (i.e., it equals one if the woman's claimed/past performance is higher than the man's and zero if the opposite is true),[20] two interaction variables that equal the subject's IAT score when the better-performing candidate is the woman (or the man) and zero otherwise, and a dummy variable indicating whether the observed information

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[18] The hypothesis being tested is H_0: fraction of women picked $\geq$ fraction of women predicted to win based on their past performance, H_a: fraction of women picked < fraction of women predicted to win based on their past performance.

[19] In the cheap talk treatment, around 18% of subjects do not update their expectation ($\varphi_{ik} = 0$) and 25% of them update as if their prior belief was completely uninformative ($\varphi_{ik} = 1$). In the past information treatment the respective numbers are 12% for $\varphi_{ik} = 0$ and 33% for $\varphi_{ik} = 1$.

[20] We excluded observations where the woman and the man have the same performance according to the new information because it is not clear whether this information confirms/contradicts the subjects' implicit associations.

Table 2 –

corresponds to the cheap-talk (=1) or the past-information (=0) treatment. We ran a regression for all subjects and then a separate regression for each gender (see Table 2).[21]

Subjects with a high IAT score update significantly more in cases where they observe information that conforms with their implicit association (the man is the better-performing candidate) compared to subjects with a low IAT score (p = 0.028) and compared to cases where they observe information that contradicts their implicit association (the woman is the better-performing candidate, p = 0.010). As seen in Table 2, this relationship between the IAT score and updating is driven by women and not men. As one would expect, subjects consider the candidates' past performance to be more informative than the candidates' claimed performance.

4. Conclusions

In this paper, we provide evidence of discrimination against women that is neither taste-based, nor driven by a statistical inference that is justified by actual differences in performance, and instead, it is rooted in a biased belief about women's abilities. In spite of equal performance, only about one woman

[21] We use OLS estimates with robust standard errors and subject random effects. Moreover, we excluded observations with negative values for φ_{ik} since these subjects seem to be updating irrationally (less than 3% of all observations correspond to $\varphi_{ik} < 0$).

is chosen for every two men.[22]

We also observe the paradoxical result that more information in the form of self-reports leads to a worse outcome (from the perspective of gender equality)

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Appendix A – Experimental procedures and instructions

This section is divided as follows. In subsection A.1, we describe in detail the procedure followed to run the experiment. In subsection A.2, we reproduce the instructions used in the first part of the experiment and in subsection A.3 , Parts 3, 4, and 5 are repetitions of part 2. The only difference is that when selecting the candidates, only subjects who had never been a candidate in a previous part could draw a card from the deck. In other words, a subject could be a candidate at most once.

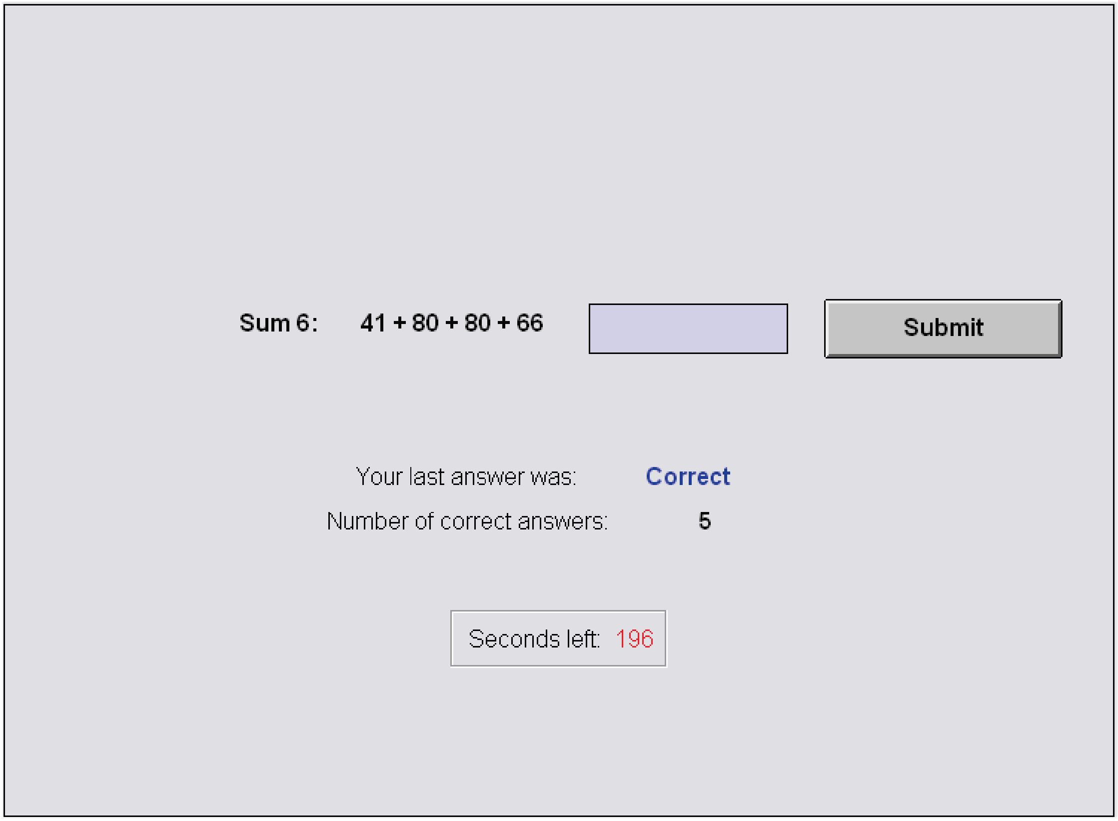
Once part 5 had finished, we used the deck of cards to randomly select a part to be paid (one of the subjects in the session drew one out of five cards). If the part to be paid was not part 1, we used the deck of cards once again to determine the decision to be paid (another subject in the session drew one out of six cards). Next, the two candidates of the part that was randomly selected for payment were asked to add sums for four minutes (other subjects could watch the candidates' progress on their screens). Thereafter, subjects were paid their earnings and dismissed.

A.2 Instructions for part 1

In part 1, you can earn money by performing a series of sums of four randomly-chosen two-digit numbers (e.g., 15 + 73 + 49 + 30). Calculators are not allowed. You will have **four minutes** to answer as many sums as possible. The computer will record the number of sums that you answer correctly. If part 1 is the part randomly selected for payment, then you will get **$0.50 for every correct sum**. Your payment does not decrease if you provide an incorrect answer to a sum.

The screen where you do the sums looks like the one below. You submit your answer by clicking on Submit. As soon as you submit your answer you will be told if it was correct or incorrect. You can also see the total number of sums you have answered correctly. At the bottom, you see how many seconds you have left.

If you have any questions please raise your hand. Otherwise you can click the button on your screen.



A.3 Instructions for parts 2 to 5

Parts 2 to 5 are identical. Before each part, two participants will be selected at random. We will call them **contender A** and **contender B**. We will call the rest of you **observers**.

Specifically, everyone will draw a card from the deck on the table. Contender A will be the one who draws the **red ace** and contender B will be the one who draws the **black ace**. Each participant gets to be a contender at most once. Hence, in parts 3 to 5 those of you that were contenders in previous parts will not draw a card and will play as observers.

Contenders

As mentioned, at the end of the study, we will randomly select a part to be paid. If part 2, 3, 4, or 5 is selected, the two participants that were Contender A and contender B in the selected part will have another four minutes to answer sums. This time, however, their earnings depend on their relative performance. The contender who correctly answers the most sums will be the **winning contender**. In case of a tie, one contender will be randomly selected as the winner. The winning contender earns **$18** and the other contender earns **$0**.

Note that both contenders will face the same sequence of randomly generated sums. That is, they will face the same difficulty.

Contenders can earn additional money depending on the decisions of the observers. This is explained further down.

Observers

In each part, observers make **six decisions**. Decisions consist of either: (i) accurately guessing the number of sums that each contender answers correctly, or (ii) picking the winning contender.

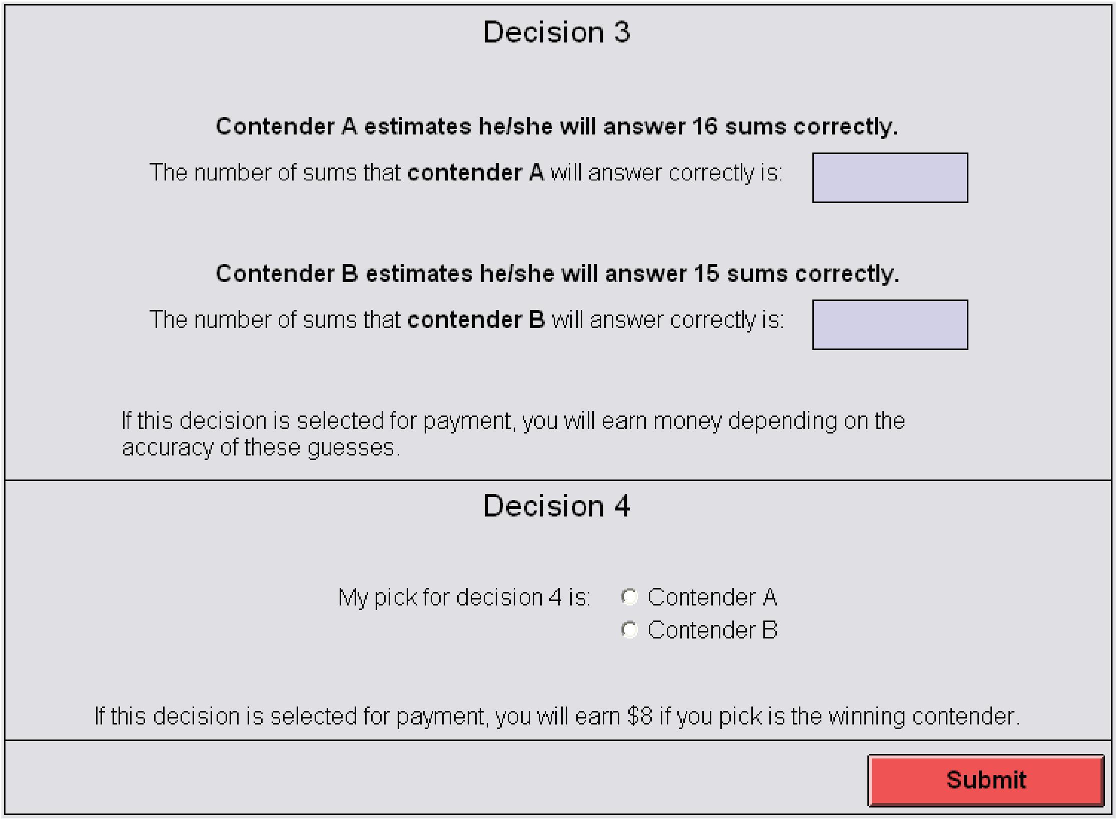
Once a part is selected for payment, **one of the six decisions** in that part will be picked at random to determine your final payment. Each decision is explained in detail below.

Observers: Decisions 1 and 2

If you are an **observer**, you will make decisions 1 and 2 on the following screen:

On the top part of the screen, you make **decision 1**. This decision consists of guessing the number of sums that each contender will answer correctly. Your earnings depend on the accuracy of your guesses according to the table below.

Difference between your guess and the number of sums answered correctly	Earnings for your guess (per contender)
0 sums away (exact answer)	$4.00



On the top part of the screen, you make **decision 3**. You are asked once again to guess the number of sums that each contender will answer correctly. Your earnings depend on the accuracy of your guesses according to the same table as in decision 1. Note that, unlike in decision 1, you can also see the **answers submitted by each contender to the abovementioned question**.

On the bottom part of the screen, you make **decision 4**. Again, you are asked to pick one of the two contenders. If the contender you picked becomes the winning contender, you earn **$8**. If your pick does not become the winning contender, you earn **$4**.

Additional earnings for contenders

As before, contenders earn additional money depending on the number of observers that pick them. If observers are paid according to decision 3 or 4 in a given part, every observer that picks contender A in this screen, increases A's earnings by $1. Similarly, every observer that picks contender B in this screen, increases B's earnings by $1. Contenders receive the additional earnings independently of whether they win or not.

Observers: Decisions 5 and 6

If you are an observer, you will make decisions 5 and 6 on the following screen:

On the top part of the screen, you make **decision 5**. You are asked once again to guess the number of sums that each contender will answer correctly. Your earnings depend on the accuracy of your guesses according to the same table as in decision 1. Note that, unlike in decision 1 3, you cTc

Example of how to calculate earnings

Suppose that you are an observer in part 2 and that this part is picked for payment. Furthermore, in decision 1 you guessed that contender A will answer 10 sums correctly and contender B will answer 14 sums correctly. In decision 2 you picked contender B.

If it turns out that contender A answered 8 sums correctly and contender B answered 11 sums correctly, then:

If decision 1 is selected for payment, your earnings would be: $3.56 for your guess of A's performance + $3.00 for your guess of B's performance + the $12.00 show-up fee = $18.56.

If decision 2 is selected for payment, your earnings would be: $8.00 for picking the winning contender + the $12.00 show-up fee = $20.00.

For the earnings of contenders, suppose that in addition to you, contender B was picked by 5 other observers in decision 2 and contender A was picked by 4 observers in decision 2. In this case, if decision 1 or 2 are selected for payment, Contender B's earnings would be: $18.00 for being the winning contender + $6.00 for being picked by 6 observers + the $12.00 show-up fee = $36.00, and contender A's earnings would be: $0.00 for not being the winning contender + $4.00 for being picked by 4 observers + the $12.00 show-up fee = $16.00.

Final note

Note that when they perform the sums, contenders will **not know** how many observers have picked them. This will be revealed after they finished answering sums. Contenders will not know at any point what the guesses of the observers were.

If you have any questions please raise your hand. Otherwise you can click the button on your screen.

A.4 Implicit association test

We used the IAT introduced by Greenwald, McGhee, and Schwartz (1998). In particular, we asked subjects to associate pictures to the categories "male" or "female" and to associate words to the categories "math and science" or "liberal arts." The precise words used for "math and science" are: physics, engineering, chemistry, biology, statistics, geometry, calculus, and algebra, and the words used for "liberal arts" are: literature, music, philosophy, writing, history, arts, civics, and humanities. Pictures are not reproduced in this document due to copyright but are available upon request. Figure A1, provides a sample screenshot of the IAT.

The IAT serves as an indirect measure of associations between different categories (in contrast to directly asking subjects to self-report them). The advantage of the IAT over self-reported measures is that in socially sensitive domains

Appendix B – Additional data analysis

In this section we provide additional figures and tables to support the data analysis described in the main body of the paper.

Figure B1 shows the cumu6 0 Td(1) th dt6- 1(t)1(i)-1(r)31(e)r(s)-2(1-1(es)ui)61(o)-4(n)-1(a)-3(l)--3(ec)2( )-5(t)1

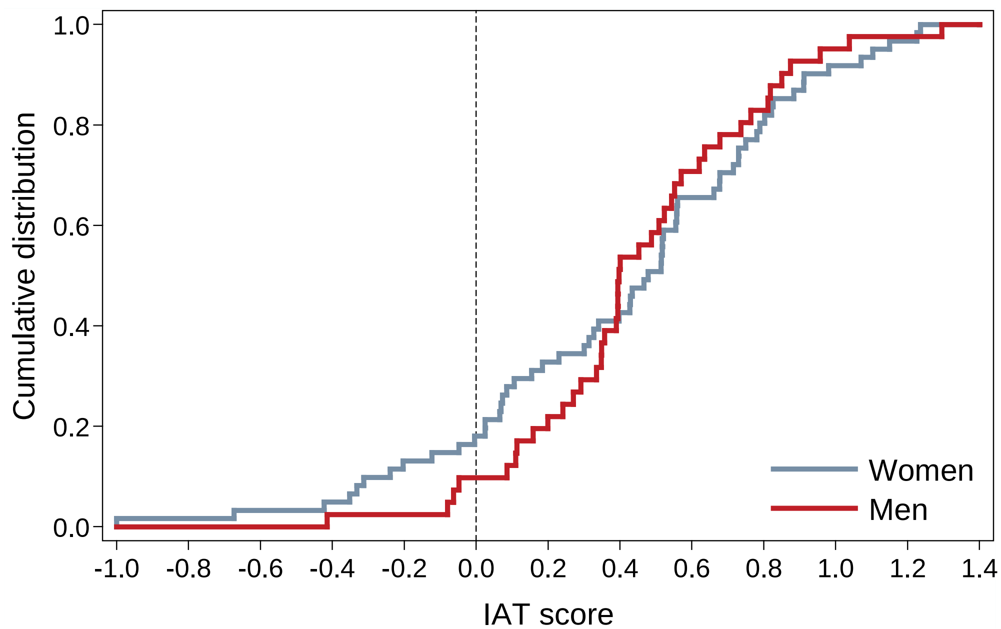


Figure B2 – Cumulative distribution of IAT scores by gender

Table B1 reports the regression used to construct Figure 1 in the main body of the paper. The dependent variable is the difference between a subject's expected performance of the female candidate and the subject's expected performance of the male candidate. We use data only from parts in which candidates were of different genders. As independent variables we use the subject's IAT score, a dummy variable indicating the (choosing) subject's gender and a slope-dummy variable interacting gender and IAT score. We use OLS estimates with robust standard errors. Moreover, we include subject random effects and session fixed effects (to control for the candidates' other characteristics). In total, we have 136 observations, for 78 subjects (between 1 and 4 observations per subject), and 14 sessions (between 3 and 27 observations per session).

Table B1 – Expected difference in performance of women compared to men and IAT score

	coefficient	standard error	*p*-value
IAT Score	-2.105	1.052	0.045
Female	-1.331	0.611	0.029
Female × IAT Score	2.194	1.177	0.062
R^2	0.237		

Figure B3 shows the distribution of the variable φ_{ik} (defined in the main body of the paper) divided by whether the new information corresponds to the difference in the candidates' claimed performance or to the difference in their actual past performance. Recall that $\varphi_{ik} = 1$ corresponds to the case where the subjects' updated belief equals their new information (i.e., their prior belief is completely uninformative), and $\varphi_{ik} = 0$ corresponds to the case where beliefs are not updates at all (i.e., the new information is completely uninformative).

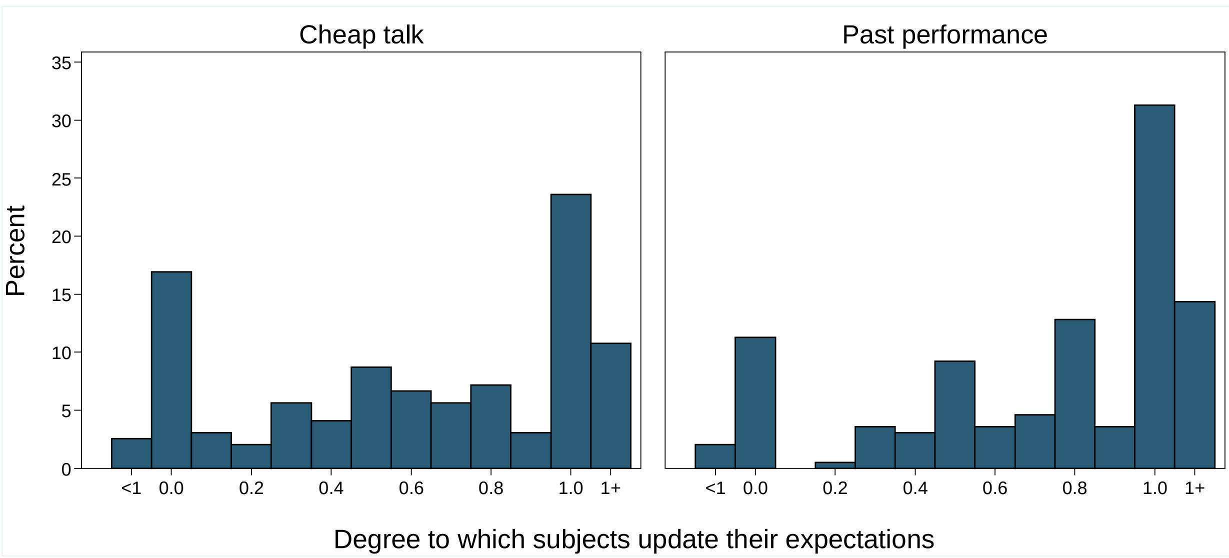


Figure B3 – Distribution for φ_{ik}, which measures the degree to which subjects update their expectations of relative the performance of men and women with the arrival of new information

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