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Affirmative Action and Application Strategies: Evidence from Field Experiments in Colombia

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Abstract
Affirmative action changes incentives at all stages of the employment process. In this paper, we study the effects of affirmative action statements in job ads on i) the effort expended on the application process and ii) the manifestation of emotions, as measured by the textual analysis of the content of the motivation letter. To this end, we use data from two field experiments conducted in Colombia. We find that in the *Control* condition, women spend less time in the application process relative to men. Besides, female motivation letters exhibit lower levels of emotion, as measured by valence, arousal, and dominance. However, those differences vanish in the affirmative action treatment when we announced to job-seekers that half of the positions were reserved for women. In the *Affirmative Action* condition, the time dedicated by women significantly increased and the motivation letters written by the female candidates showed a significant increase in the expression of positive emotions. The results indicate that affirmative action policies can have significant encouraging effects on both effort and appeal of job applications of women, thereby reducing the gender gap in these outcomes. (JEL: C91, J15, M52)

Keywords: Gender, Labor economics, Field experiment.

1. Introduction

Affirmative action (AA) is often a contested policy in the quest for more diversity within organizations. Critics argue that such policies could result in reverse discrimination and loss of efficiency (Coate and Loury, 1993; Welch, 1976), which is undesirable from a deontological and economic perspective. In this paper, we revisit the question on the impact of AA by analyzing the consequences of this policy in the provision of effort and self-presentation of job

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seekers in the context of a real job offer. The behaviour at the application stage itself is relevant as it determines the appeal of the applicant, the probability of being employed, and influences the quality of a match.

What effect can we expect from affirmative action statements in job advertisements on our outcome variables? Economic theory provides diverse predictions on the impacts of affirmative action on ex-ante effort provision (Fang and Moro, 2011). For example, Coate and Loury (1993) show that affirmative action can decrease incentives for ex-ante effort if the employers fill the quotas by assigning the intended beneficiaries to less skilled jobs. Similarly, Franke (2012) shows that AA can cause inefficient outcomes when there is considerable heterogeneity in qualifications between beneficiaries and non-beneficiaries of the policy. However, affirmative action policy can have positive effects on ex-ante effort provision when both groups have equal opportunity to win the competition (Fain, 2009) and when affirmative action increases competition (Balart, 2011).

Moreover, AA can also influence self-presentation. As people build mental models of decision situations and interpret cues according to long learned patterns (Hoff and Stiglitz, 2016), AA can influence the language used in a job application context. As women perceive fair treatment and increased chances of being employed, these cues can lead to more positive views of the job and increase a female applicant's confidence.

We address this question using two large field experiments with 4480 job-seekers in Colombia. Despite remarkable progress in reducing educational gender gaps and increasing female labor force participation, women still face worse employment prospects than men in most of the countries. According to the 2018 data from the UNESCO Institute for Statistics and ILOSTAT, in Colombia, women represented a larger share of enrolled students in secondary and tertiary education (51.2% and and 53.9%, respectively). However, women are 30 percent less likely to participate in the labor market, receive on average 11 percent lower wages, and have a 2 percentage point higher unemployment rate than men (Cepeda Emiliani and Barón, 2012).

Similar to Flory et al. (2015), we use an online recruitment strategy that proceeds in two steps. First, we build a database with over four thousand job-seekers who are interested in supporting field data collection in Colombia. At this stage, we obtain the job-seekers' basic socioeconomic characteristics such as gender, residence, area of study, and the number of years of experience. In a second step, we invite all job seekers to apply to the position by completing a longer application process. We vary the information that we give such that half of the job-seekers are informed that the employer is an equal opportunity employer and that at least half of the hired assistants will be women. The rest of the participants receive this information only after they submit the application form. This randomized treatment design allows us to examine the effect of affirmative action, while maintaining the ex-post information content in the two treatments identical. We compare (i) the language the applicants used to present themselves in their motivation letters using techniques from natural language processing (NLP) and (ii) the effort they spent during the application procedure. Both of our outcomes of interest influence hiring decisions and hence, contribute to the differential allocation of jobs over gender.

To assess the emotional content of an applicant's language, we apply a popular natural language processing technique—sentiment analysis—on the letters of motivation and estimate how AA affects written emotional states, particularly with respect to valence, arousal, and dominance.[1] Using this method, we can assess how applicants self-presentation is affected by AA. The second metric we use is how diligently job seekers engage with the application that we proxy with minutes invested in filling out the form. Besides, we use alternative measures of effort such as the proportion of questions they answered, the proportion of pages they visited, and whether the applicant had visited the last page of the application form or not.

Do AA statements have heterogeneous effects on women and men? We find that in the absence of affirmative action, women exhibit lower levels of emotion in the statement of motivation and spend less effort in the job application process compared to men. While women spent the same time as men filling the application, they visited a lower proportion of pages, answered a lower proportion of questions, and were less likely to visit the last page in the control condition. The AA treatment significantly increases the degree of emotion and effort that women put into the application process relative to the baseline, suggesting that it changes job seeker perception of the decision situation. Affirmative action leads to a significant reduction in the gender gap in effort and self-presentation of applicants in the application process and has no adverse effects for male job seekers.

Our paper contributes to various strands of the literature. First, laboratory-based experiments showed that AA can help to reduce gender gaps in selection in competitive environments, attracting relatively more skillful candidates and without discouraging the ones 'penalized' by affirmative action (Niederle et al., 2013; Balafoutas and Sutter, 2012; Beaurain and Masclet, 2016). Moreover, AA did not reduce effort or cooperativeness irrespective of whether the rule is exogenous or endogenously selected (Dulleck et al., 2017; Calsamiglia et al., 2013; Balafoutas and Sutter, 2012; Balafoutas et al., 2016). However, there is relatively little field evidence on the impact of affirmative action policies on sorting in the labor market. Leibbrandt and List (2018) found that AA statements can backfire, reducing applications from the ethnic minority groups they intend to benefit. However, using field experiments, Ibanez and Riener (2017) demonstrated that AA (quotas or preferential treatment) is effective at closing gender gaps in application submissions and that this was not associated

1. The partition of emotions into these three parts goes back to Mehrabian and Russell (1974) For a review of the literature on sentiment analysis based on texts, see Khan et al. (2016).

with sorting out of the most qualified job seekers. We extend this line of research to consider the effect of AA statements on the effort put into the job application process.

Second, while recent experiments studied interventions which reduce search costs for the unemployed (Kircher et al., 2015) or looked at changes in the search requirements (Arni and Schiprowski, 2019), there is very little research on gender differences in effort provided during the application process. This gender gap, distinct from the gender gap in representation arising out of selection, may have an important effect on the subsequent differences in competitiveness. Our finding shows that there are significant gender gaps in effort during the job application process. This is important as it suggests that gender gaps in representation are observed not only at the extensive but also at the intensive margin. AA statements not only affect selection attracting more women, the women who choose to apply, exert more effort. The reduction in the gender gap, in the presence of affirmative actions, may go a long way in helping us understand the mechanisms through which such policies help increase greater representation of women in jobs.

We also contribute to the application of text analysis to economics (see review articles by Algaba et al., 2020; Gentzkow et al., 2019a; Varian, 2014; Kumar and Jaiswal, 2020). Text analysis has been used to predict stock markets (Tetlock, 2007; Das and Chen, 2007; Chen et al., 2014; Jiang et al., 2019; Siganos et al., 2014), proxy corruption, discrimination and geopolitical risks (Groseclose and Milyo, 2005; Gentzkow et al., 2019b; Saiz and Simonsohn, 2013; Campante and Do, 2014; Stephens-Davidowitz, 2014), and predict economic activity and employment (Baker et al., 2016; Da et al., 2015). However, little is known about how job advertisement changes the applicants' use of language in their motivation letters. Textual features may contribute to success in job application and evaluation. For example, Brandt and Herzberg (2020) found critical language, use of prepositions and short text to be positively correlated with success in job placement, while Abe (2009) shows that positive evaluations of interns are linked to the use of positive language in their written samples. We employ sentiment analysis—a technique from the toolkit of NLP—to analyze the content of motivation letters of job applicants and the effects of AA on the same.

The remaining paper is organized as follows: Section 2 describes the literature and lays out the research hypotheses. Section 3 presents the research design and the main experimental treatment. Section 4 presents the key results while Section 5 offers concluding remarks.

2. Experimental Design and Procedures

Our data comes from two independent field experiments conducted in Colombia. In both experiments, we recruited research assistants to work on collecting data for research projects of two of the coauthors of this paper. The experiments were similar in content and structure, but were implemented in two different years. We refer to them as Assistant 1 and Assistant 2 experiment, respectively. The recruitment strategy used in the experiments is similar to Flory et al. (2015) and, as described in detail in Ibanez and Riener (2017), comprises two main stages.

Stage 1: Recruitment of Job Seekers

To build a pool of job seekers, we announced the positions through newspapers, university employment boards, social media, and email lists. We provided general information about the positions to attract a large pool of job seekers interested in the positions. In particular, we informed that we were recruiting research assistants who had completed or were close to completing a bachelor's degree in any area of study. No previous work experience was requested. Job-seekers were asked to fill out a statement of interest form. The announcement elicited great interest and in the experiments 4480 individuals expressed interest in the position.

Stage 2: Recruitment of Job Applicants

In this stage, we gave all job seekers detailed information on the conditions of employment, job responsibilities, salary, and duration of the contract. In addition, the sample of participants who were randomly allocated to the affirmative action treatment (AA) received the information that the employer was an equal opportunity employer and that half of the positions were reserved for women. Job-seekers in the AA treatment saw the following statement (translated from Spanish):

> The University of [...] is an equal opportunity employer. To increase female participation in areas where women are up to now underrepresented, a minimum of 50% of the hired assistants will be women.

We stratified treatment assignment based on participants' gender (male or female), degree of study (master or not), and area of residence (Bogota or not). To achieve ex-post equality of information, participants allocated to the control group received information on equal opportunity policies only after completing the application process. Variation of the time when job-seekers received information on the use of affirmative action policies allows us to causally identify the impact of affirmative action statements without any difference in the final information available in the two treatments.

In this stage, job-seekers could start filling out a lengthy application questionnaire. They had access to a personalized page and could complete the application form over different sessions, saving the information and continuing the application over several days. However, a strict deadline was set after which no application was accepted.

To complete the application, participants needed to obtain supporting information such as grade certificates or detailed information on previous employer contact information, write a motivation letter, and perform various tests of qualification. This demanding and time-consuming stage increased the cost of the application (time required). We interpret this time spent on the application as a measure of the effort that participants put in completing the application (preparing to compete in the selection process).

The top 10 applicants were invited for an interview. In the Assistant 1 experiment, three candidates (all of them women) were employed. In Assistant 2, we hired 22 applicants, half of whom were women. Field experiments that go over multiple sessions and that are not conducted at the same time could suffer from information spillover. We tried to minimize this by opening the position at the same time and by recording the starting time of the applications, to control for potential timing effects.

2.1. Outcome variables

The outcome variables can be grouped into two broad categories: (i) the motivation letter and (ii) measured engagement with the application form.

Motivation letter. Applicants where requested to write a motivation letter arguing why they could be good candidates for the job. We use Natural Language Processing (NLP) techniques to analyze the emotional state of the applicant, as perceived from the contents of the motivation letter. We perform sentiment analysis by using a standard library to assign scores of valence, arousal and dominance on each word and phrase found in the text of the statement of motivation (Warriner et al., 2013). While valence gives a measure of how pleasant a word or a phrase is, arousal and dominance measure the intensity of emotion and the degree of control, respectively.

Engagement with application procedure. We have four measures of the applicant's engagement with the application process. We recorded the *time* for which the applicants had each page of the application questionnaire open. Time invested in the application process is a good proxy of effort as the unique format of the questionnaire meant that it was impossible for candidates to simply copy the contents of their curriculum vitae on to the questionnaire. Many sections required applicants to search for detailed information and input it separately. Besides, Calafiore and Damianov (2011) show that time spent on e-learning web-platform is associated with better test scores. To assess whether subjects *reached the last page* of the application questionnaire, we used an indicator variable equal to one for participants who reached the final page. This includes participants who visited the page but might have not completed the full application. This variable also acts as a proxy for effort as participants might scroll through the pages to better prepare to complete the application.

We also record the *proportion of questions completed.* The two experiments used slightly different versions of the application form. To account for this difference, we use as outcome variable the proportion of questions filled. As participants provided more detailed information, the employers can better assess the quality of the candidates. Moreover, more experienced candidates would have additional information to provide. The last indicator we use is the *proportion of pages visited*: Participants could complete up to 7 pages in Assistant 1 and 5 pages in Assistant 2, this measure captures how far participants progressed in preparing the application.

2.2. Hypothesis

Completing a job application is costly in terms of the time spent in the process, but can be associated with a higher probability to be employed. Agents will select the optimal level of effort to maximize the expected utility:

$$v = \pi(e)w - c(e)$$

In the optimum, the marginal return to effort is equal to the marginal cost of effort: $\frac{\partial \pi}{\partial e}w - \frac{\partial c}{\partial e} = 0$. Since our sample comprises mainly students in their last year of undergraduate education, it is reasonable to assume that the marginal cost of effort is similar across genders. However, in a discriminatory labor market that —on average— favors male candidates, women on average expect a lower likelihood of being employed $\pi_f < \pi_m$ and lower wages $w_f < w_m$ than male job seekers. When a non-discriminatory firm does not signal its type, we can therefore expect that women would be less likely to invest effort in completing the application. First, the marginal return to effort is lower $\partial \pi / \partial e$. Second, the marginal value of effort is lower $w_f < w_m$. We hypothesize:

HYPOTHESIS 1. *In the baseline treatment, female applicants provide lower effort than male applicants.*

If indeed women anticipate discrimination in the labor market, they may get discouraged and consequently, invest lower effort in the job application. Firms that voluntarily use AA policies signal a non-discriminatory type, increasing the perceived chances for women of being employed compared to firms that do not signal the preference for gender equity. This can lead to an increase in the effort that a female applicant puts in the job application, which leads to our next hypothesis.

HYPOTHESIS 2. *The amount of effort provided by women in the job application process is higher in the presence of affirmative action.*

Given role expectations under standard recruitment procedures (Hoff and Stiglitz, 2016), we expect that women use less positive language in all three dimensions in their motivation letter compared to men.

Hypothesis 3. *Women manifest a lower set of positive affective emotions in the motivation letter than men in a standard recruitment procedure.*

Affirmative action changes the social environment as it may signal a different set of expectations on the appropriate level of positive emotions in language of the protected group and hence increases the emotional count of their language. Hence, we formulate the following hypothesis:

Hypothesis 4. *Women show a larger set of positive affective emotions within the motivation letter in the presence of an affirmative action compared to a standard recruitment procedure.*

3. Results

3.1. Summary statistics of the two experiments

In the first stage, following the job announcements, we received the statement of interest from 4480 people (2217 and 2263 people for Assistant 1 and Assistant 2, respectively). Half of the applicants for each position were assigned to the affirmative action treatment condition, with about 55% females in Assistant 1 and 50% females in Assistant 2. In the second stage, 2144 job seekers started the application process. In Assistant 1, about 55% of the job applicants were female, while in Assistant 2, 49% were female. Our main interest in this paper is to analyze the gender differences in the effort for job application at this stage. Table A.1 in the Appendix gives a detailed account of the statistics related to the recruitment process at each stage.

Table A.4 in the Appendix presents the treatment-wise demographic characteristics of the participants in each stage according to whether they started the application process. We separately test whether the observable characteristics are different between control and treatment within each stage and report the p-values in Col (5) and (6). We find no evidence that the treatment and control are systematically different on the basis of the observable characteristics in either of the two treatments in stage 1. Moreover, we compare the observable characteristics of job applicants versus job seekers (Stage 2 vs. Stage 1) and report the p-values in columns (7) and (8) for the control and treatment groups, respectively. We find that the p-values are less than 0.05 for a few observables[2], suggesting that there is some evidence of selection. To address this issue, the regression analysis on the intensive margin effects uses inverse probability weights following Wooldridge (2007). This method has been

2. Throughout the paper, we report two-sided tests and refer to results as (weakly/highly) significant if the two-tailed test's p-value is smaller than 0.05 (0.10 / 0.01).

widely used in the literature to account for the problem of non-random sample selection (Elfenbein et al., 2010; Fitzgerald et al., 1998).

3.2. Treatment differences in the main outcomes of interest

In the analysis, we pool data from Assistant 1 and Assistant 2 experiments and estimate the following linear probability model:

$$Outcome_i = \alpha + \beta_1 AA_i + \beta_2 Female_i + \beta_3 AA_i \times Female_i + \beta_4 X_i + \varepsilon_i$$

where $Outcome_i$ represents the following four metric measuring effort of the i^{th} individual in our set-up: duration of time spent on the application (standardized), whether the last page has been visited, the proportion of questions filled out, and the proportion of pages visited.[3] AA_i is a dummy variable indicating whether the participant was in the treatment group and $Female$ takes value equal to one for female participants and zero otherwise. Our main parameters of interest are β_1 and β_3, which measure the effect of Affirmative Action (AA) on male applicants and the gender gap, respectively. Additional control variables included in the vector X are a dummy variable indicating whether the observation is from Assistant 1 or 2, applicant's age, and whether the applicant holds a master's degree.[4]

First, we estimate the model considering the pool of all job seekers, i.e., all those who expressed interest in the position following the job announcement. In this case, the outcome variables take the value zero for those who did not start the application process.[5] Thus, the estimation captures the total effect on the extensive and intensive margin of effort provision. Second, to focus on effort provision on the intensive margin, we estimate the model only with the pool of job applicants, i.e., those who participated in stage 2 of the application process where they would fill out an application questionnaire. Here, to address the issue of selection, if any, between stage 1 and stage 2, our estimation uses the inverse probability weighting method. Hence, the observations are weighted by inverse of the probability of occurrence in stage 2.[6] Further, we follow

3. We use the mean and standard deviation of the male applicants in the control group to standardize the outcome variable (i.e. calculate the z-score) wherever relevant.

4. As a robustness test we estimate the model separately for Assistant 1 and 2 where we include additional control variables specific to the experiment.

5. We present OLS estimates in the main tables as we are interested in the average marginal effects of AA treatment by gender, for which linear models are suitable (Angrist and Pischke, 2008). However, in a robustness analysis we also estimate other appropriate nonlinear models such as tobit, probit, and fractional probit and present the results in the Appendix. The results are not sensitive to the choice of models.

6. We obtain the probability of selecting into stage 2 by taking the entire sample and estimating a probit model that includes AA, all the control variables including gender, and

Young (2018) and use randomization statistical inference to test for overall experimental significance. The reported p-values in the figures and tables are corrected using Young's *randcmd* command in Stata. In terms of the number of hypotheses we correct for, we have of four outcomes analyzed in Table B.1, three in Table C.1 and two additional outcomes in Table D.1. We test three coefficients (AA, Female, AA$\times$Female) for each and this gives us a total of 27 hypotheses, for which we correct the p-values.

Panel A in Figure 1 presents the estimated coefficients for the total effects and Panel B presents the estimated coefficients for the intensive margin effects.[7]

Qualitatively, the results are similar irrespective of whether we focus on the total effort (Panel A) or effort on the intensive margin (Panel B). The results suggest that in the absence of AA policy, women are significantly less likely to visit the last page, fill out a lower proportion of questions, and visit a lower proportion of pages than males, providing support for Hypothesis 1. When AA is introduced, females, relative to males, increase the amount of time they spend in filling out the application by 20.4% of a standard deviation and this is significant at 1% level (col (2)). Likewise, the likelihood of visiting the last page increases by 5.8 percentage points for females compared to males due to AA treatment. Considering the proportion of questions filled out and the proportion of pages visited by the applicants, we find that gender parity increases by about 3.7–3.9 percentage points under AA treatment, with the estimates being significant at the 5% level. This result is in line with Hypothesis 2. While there is greater gender equality in effort provision, are the corresponding outcomes of males adversely affected by AA treatment? Other than the amount of time spent in filling out the application form, we did not find evidence that men put less effort in the AA treatment. Overall, the results from Table B.1 suggest that AA closes the gender gap in effort provision during the application process relative to the baseline.

We present the results separately for Assistant 1 and 2 in the Appendix in Tables B.2 and B.3. We broadly find similar patterns suggesting that females spend significantly less effort on job application relative to males in the absence of AA, especially in the Assistant 1 experiment. The AA treatment changes the direction of the gender gap in favor of females in both experiments, with the

their interactions. The inverse of the predicted probabilities for each observation is used as weights while estimating the regressions to capture effort on the intensive margin. We also get similar results when we don't use inverse probability weights; these results are available on request.

7. Panel A in Table B.1 reports the estimation results for the complete sample, while Panel B present the results for the sample that began the application process. For each outcome of interest, we present the results with and without the socioeconomic controls.

effects being more precise for the Assistant 2 experiment. The point estimates are also very similar to those obtained in Table B.1.[8]

As discussed in Section 2, respondents in Assistant 1 are asked to write a statement of motivation as a part of their application. We perform sentiment analysis to assign scores of valence (pleasantness), arousal (the intensity of emotion provoked), and dominance (the degree of control exerted) to the application letters. The scores are then demeaned and divided by standard deviation to make them comparable. We then estimate Equation 3.2 using the standardized scores as the dependent variable. Figure 2 presents the estimated coefficients for the total effect (Panel A) and intensive margin (Panel B), with corrected p-values for multiple hypothesis testing.[9] We report the results of the specification that includes demographic controls and the total number of words in the motivation letter. The results show that in the absence of AA, the motivation letters written by females systematically exhibited lower valence, arousal, and dominance than the ones written by males. This is consistent with existing literature in psychology, which finds that women adopt significantly more emotion regulation strategies in communication compared to men (Nolen-Hoeksema, 2012; Tamres et al., 2002), and supports Hypothesis 3. The AA treatment decreases the gender gap in the emotional value of the motivation letter. In particular, valence increased by 7.3%, arousal increased by 7.9%, and dominance increased by 6.3% of a standard deviation for females compared to males, as a response to the AA treatment. Correcting for multiple hypothesis testing, we find that at the intensive margin, the treatment effects of AA on valence and arousal are significant at the 5% level, while that of dominance is significant at the 10% level. Hence, the results provide support for Hypothesis 4 and indicate that the statements of motivation written by females in the AA treatment exhibited more pleasantness and intensity of emotion. These attributes are significant predictors of how an applicant is viewed by an employer and eventually how successful the job applicant is (Abe, 2009; Brandt and Herzberg, 2020). Overall, women exhibit higher emotions in the AA treatment and this may be a result of encouragement due to the fact that an AA policy is in place. AA has no significant effect on male applicants' sentiments in the motivation letter.

8. The fact that the point estimates are directionally consistent, quantitatively similar but sometimes statistically insignificant indicates that the tests are possibly under-powered when conducted separately for Assistant 1.

9. The estimation results are reported in Table C.1. We use three types of specifications: one that does not include any control variables, including demographic controls, and including the total number of words present in the statement of motivation.

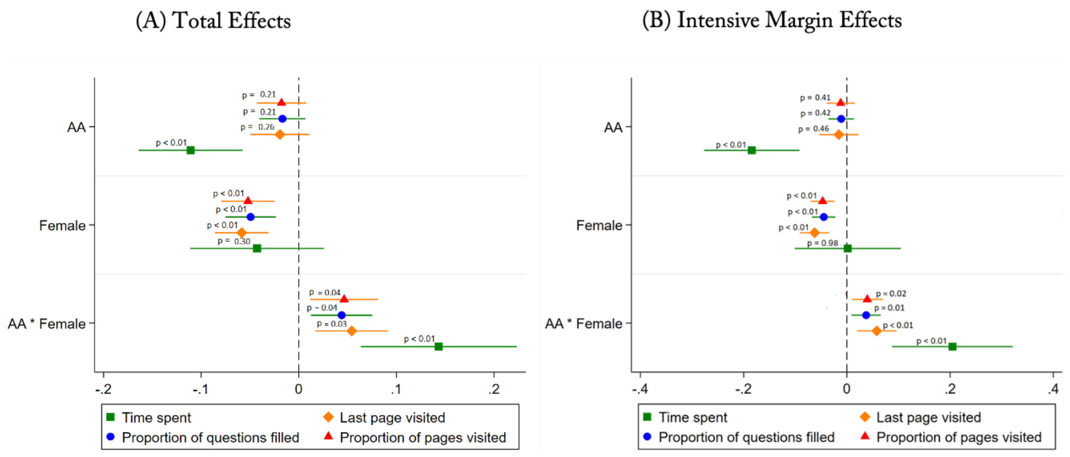

Figure 1. Effect of Affirmative Action treatment on application-effort in Assistant-Pooled

Note: The figure plots the treatment effects of Affirmative Action in the Assistant-Pooled data. Panel (A) plots the coefficients for the total effects (or ITT) by including those who did not fill out the application eventually. Panel (B) plots the coefficients for the intensive margin effects by excluding those who did not apply. The regressions control for age and a dummy for masters' degree. The p-values are obtained using randomization inference (Young, 2018) and are corrected for multiple hypotheses testing using Westfall-Young multiple-testing methods.

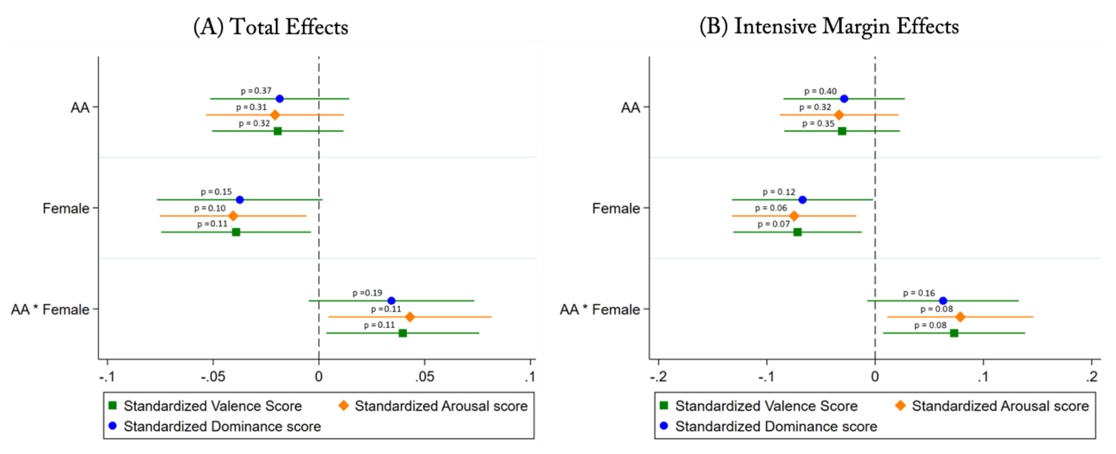

Figure 2. Effect of Affirmative Action treatment on sentiment in Assistant-1

Note: The figure plots the treatment effects of Affirmative Action on sentiments in the Assistant-1 data. Panel (A) plots the coefficients for the total effects (or ITT) by including those who did not fill out the application eventually. Panel (B) plots the coefficients for the intensive margin effects by excluding those who did not apply. The regressions control for age and a dummy for masters' degree. The p-values are obtained using randomization inference (Young, 2018) and are corrected for multiple hypotheses testing using Westfall-Young multiple-testing methods.

4. Discussion and Conclusion

The effort and diligence shown by applicants in the job application process are often important signals for employers and shape their hiring decisions. However, the job advertisement itself may influence a job seeker's motivation to engage with the job application. We investigate how affirmative action statements within application procedures influence the effort put into the application process and the style of the motivation letter.

Our findings show that there is a significant gender gap in applicants' effort and motivation in job applications. Without affirmative action, female job seekers engage less in the application procedure than males. Besides, female job seekers use language that is less dominant and shows lower levels of valence and arousal, which can be interpreted as having lower confidence. Hence, differences in application could partly help to explain the gender gaps in the employment of otherwise equivalent candidates. Affirmative action compensates for this difference by encouraging women to put in more effort and boosting confidence among women. The incentive effects for men are smaller in size and statistically indistinguishable from zero, indicating that the cost of affirmative action at this margin is low. This suggests that affirmative action policies positively influence female engagement in the application process, leading to a more favorable self-presentation that is likely to result in better chances of being hired.

We identify directions for future research to better understand the behavior of applicants under affirmative action. A caveat of our study is that while the first stage of our experiment aimed at recruiting a large pool of applicants, we cannot rule out that women might have been discouraged in the first stage itself. If that is the case, our study might underestimate the initial gender gap in effort and confidence in the application. The context of our study considers a typical middle income country, where women on average reach a higher education level than men. In this framework, the effect of AA policies is to increase competition among participants who otherwise have equal changes to get employed. As implied by the theoretical models of Fain (2009) and Balart (2011), our findings confirm that AA increases incentives to provide effort. Future work should assess the validity of our results in contexts where there is more heterogeneity between beneficiaries and non-beneficiaries of AA in terms of the level of education.

One explanation of the gender difference in language use is brought forward by Hoff and Stiglitz (2016). As subjects may interpret decision situations according to contextual factors, AA might lead them to perceive the environment differently and change self-presentation. Whether this is due to strategic considerations of the applicant or a subconscious reaction to affirmative action statements, we can not determine and hence should be subject to further investigation. In job applications, candidates are confronted with different expectations of role-conforming behavior: While assertiveness often is considered important to be successful in a job, it is seen as an asset for male applicants only (Brescoll and Uhlmann, 2008). This poses a dilemma for female candidates: Although job-relevant, showing increased levels of emotion at presentation may reduce the chances of obtaining a job. This channel deserves exploration in future research, as these double standards can constitute a source of gender imbalance not only in applications, but in the job itself, posing problems for firms in managing diverse teams.

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Appendix A: Recruitment: Summary Statistics

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TABLE A.1. Recruitment Process

Stage	Assistant 1 (A1)					Assistant 2 (A2)				
	Observation				% Female	Observation				% Female
	Control	% Female	AA Treat	% Female		Control	% Female	AA Treat	% Female	
Stage 1 : Job-Seekers	1108	55.05	1109	55.28	55.16	1131	50.13	1132	50.27	50.20
Stage 2 : Job Applicants	545	54.13	553	55.15	54.64	532	48.50	533	50.28	49.39

Table A.2. Summary Statistics of Assistant 1

Variable	Definition	Mean	Standard Deviation
Female	=1 if female, 0 if male	0.55	0.50
Age	Age in years	35.64	6.42
Master	=1 if has master's degree, 0 otherwise	0.10	0.30
Coca Region	=1 if recruited for Coca region, 0 if recruited for Tobaco region	0.67	0.47
Bogota	=1 if located in Bogota, 0 otherwise	0.36	0.48
Motivation count	Number of words in statement of motivation	92.99	102.34
Outcomes			
Valence Score $\mid$ Motivation count >0*	Valence score from statement of motivation	89.60	77.77
Valence Score*	Valence score from statement of motivation, missing values replaced by 0	36.33	66.23
Arousal Score $\mid$ Motivation count > 0*	Arousal score from statement of motivation	61.64	54.28
Arousal Score*	Arousal score from statement of motivation, missing values replaced by 0	24.99	45.94
Dominance Score $\mid$ Motivation count >0*	Dominance score from statement of motivation	90.50	78.29
Dominance Score*	Dominance score from statement of motivation, missing values replaced by 0	36.70	66.78
Time Spent*	Time spent in completing the questionnaire in stage 2 (in hours)	87.82	129.00
Proportion of pages visited	Proportion of the total pages completed in the stage 2 questionnaire	0.82	0.32
Proportion of questions filled	Proportion of the total questions answered in the stage 2 questionnaire	0.78	0.33
Last page visited	=1 if visited the last page of stage 2 survey, 0 otherwise	0.36	0.48
Sample size - stage 1		2217	
Sample size - stage 2		1098	

Note: The variables marked with * have been standardized by demeaning and dividing by the standard deviation, before they were used for analysis.

TABLE A.3. Summary Statistics of Assistant 2

Variable	Definition	Mean	Standard Deviation
Female	=1 if female, 0 if male	0.50	0.50
Age	Age in years	31.61	7.14
Master	=1 if has master's degree, 0 otherwise	0.09	0.29
Relative Grade	Grade relative to maximum marks in the most recent educational program	0.84	0.09
Time Preference	Time Preference	3.28	2.04
Risk Preference	Risk Preference	5.75	2.30
CRT score	Score on Cognitive Reflective Test	1.36	1.16
Extraversion	Big 5 Personality Test Score: Extraversion	6.03	1.49
Agreeableness	Big 5 Personality Test Score: Agreeableness	4.39	1.29
Conscientiousness	Big 5 Personality Test Score:Conscientiousness	9.41	1.01
Neuroticism	Big 5 Personality Test Score:Neuroticism	4.29	1.48
Openness	Big 5 Personality Test Score:Openness	8.34	1.54
Outcomes			
Time Spent*	Ttime spent in completing the questionnaire in stage 2 (in hours)	0.53	0.22
Proportion of pages visited	Proportion of the total pages completed in the stage 2 questionnaire	0.45	0.50
Proportion of questions filled	Proportion of the total questions answered in the stage 2 questionnaire	0.45	0.49
Last page visited	=1 if visited the last page of stage 2 survey, 0 otherwise	0.44	0.50
Sample size - stage 1		2263	
Sample size - stage 2		1065	

Note: The variables marked with * have been standardized by demeaning and dividing by the standard deviation, before they were used for analysis.

Table A.4. Balance across treatments and stages

	Stage 1		Stage 2		Comparisons			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Control	Treatment	Control	Treatment	p-values (1) - (2)	p-values (3) - (4)	p-values (3) - (3')	p-values (4) - (4')
Assistant 1								
Female	0.55	0.55	0.54	0.55	0.92	0.73	0.54	0.94
Age	35.56	35.72	35.46	35.32	0.54	0.71	0.60	0.04
Master	0.11	0.09	0.11	0.07	0.15	0.02	0.85	0.01
Coca Region	0.67	0.67	0.61	0.65	0.99	0.15	0.00	0.20
Bogota	0.36	0.35	0.40	0.40	0.95	0.96	0.02	0.01
N	1108	1109	545	553				
Assistant 2								
Female	0.50	0.50	0.48	0.50	0.95	0.56	0.30	0.99
Age	31.69	31.53	31.21	30.77	0.59	0.25	0.04	0.00
Master	0.09	0.10	0.06	0.08	0.52	0.4	0.00	0.03
Relative Grade	0.84	0.85	0.84	0.85	0.31	0.26	0.83	0.29
Risk Preference	5.74	5.77	5.68	5.79	0.82	0.43	0.37	0.76
Time Preference	3.29	3.27	3.28	3.30	0.76	0.86	0.79	0.63
CRT score	1.37	1.35	1.48	1.44	0.56	0.55	0.00	0.01
Extraversion	5.99	6.07	5.98	6.03	0.17	0.55	0.83	0.38
Agreeableness	4.38	4.40	4.33	4.46	0.69	0.1	0.18	0.15
Conscientiousness	9.43	9.39	9.38	9.40	0.40	0.81	0.18	0.80
Neuroticism	4.30	4.29	4.23	4.24	0.92	0.90	0.19	0.33
Openness	8.34	8.33	8.23	8.36	0.81	0.18	0.02	0.55
Sample Size	1131	1132	532	533				

Note: Col (7) reports the p-values from comparing the control group in stage 2 with those who were in control group in stage 1 but not in the control group in stage 2 (denoted by (3')). Likewise, col (8) reports the p-values from comparing the treatment group in stage 2 with those who were in the treatment group in stage 1 but not in stage 2 (denoted by (4')).

Appendix B: Outcomes: Time and effort

TABLE B.1. Assistant Pooled

	Time spent (standardized)		Last page visited		Proportion of questions filled		Proportion of pages visited	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Total Effect								
AA	-0.112	-0.111	-0.020	-0.019	-0.017	-0.017	-0.018	-0.018
p-value	(0.000)	(0.000)	(0.217)	(0.208)	(0.166)	(0.161)	(0.172)	(0.167)
p-value (corrected)	(0.003)	(0.005)	(0.273)	(0.261)	(0.216)	(0.208)	(0.218)	(0.215)
Female	-0.041	-0.043	-0.058	-0.059	-0.048	-0.049	-0.051	-0.052
p-value	(0.249)	(0.220)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
p-value (corrected)	(0.329)	(0.300)	(0.004)	(0.005)	(0.011)	(0.010)	(0.009)	(0.008)
AA * Female	0.146	0.143	0.056	0.054	0.045	0.044	0.048	0.046
p-value	(0.000)	(0.000)	(0.006)	(0.005)	(0.007)	(0.007)	(0.010)	(0.009)
p-value (corrected)	(0.009)	(0.010)	(0.036)	(0.034)	(.0110)	(0.039)	(0.052)	(0.042)
Constant	0.008	0.248	0.391	0.503	0.403	0.524	0.429	0.555
p-value	(0.790)	(0.023)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4,408	4,408	4,408	4,408	4,408	4,408	4,408	4,408
R-squared	0.002	0.006	0.009	0.012	0.004	0.009	0.004	0.008
B. Intensive Margins Effect								
AA	-0.184	-0.184	-0.016	-0.016	-0.011	-0.011	-0.012	-0.012
p-value	(0.000)	(0.000)	(0.427)	(0.420)	(0.378)	(0.373)	(0.388)	(0.384)
p-value (corrected)	(0.008)	(0.008)	(0.467)	(0.457)	(0.422)	(0.418)	(0.414)	(0.415)
Female	0.002	0.002	-0.063	-0.063	-0.045	-0.045	-0.047	-0.047
p-value	(0.972)	(0.975)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
p-value (corrected)	(0.970)	(0.981)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
AA * Female	0.205	0.204	0.057	0.058	0.037	0.037	0.039	0.039
p-value	(0.001)	(0.001)	(0.004)	(0.003)	(0.012)	(0.010)	(0.011)	(0.010)
p-value (corrected)	(0.007)	(0.007)	(0.009)	(0.008)	(0.017)	(0.014)	(0.023)	(0.021)
Constant	-0.006	0.066	0.764	0.714	0.788	0.766	0.839	0.813
p-value	(0.850)	(0.559)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144
R-squared	0.007	0.007	0.075	0.076	0.056	0.056	0.055	0.055
Other controls	No	Yes	No	Yes	No	Yes	No	Yes

Note: OLS regression results for the pooled data from Assistant 1 and Assistant 2 are reported. All regressions models include a dummy for Assistant 2. Cols (1), (3), (5) and (7) report the results without controls, while cols (2), (4), (6) and (8) report the results with controls. The control variables include the applicant's age and whether the applicant holds a master's degree. The estimates in the second panel (intensive margin) are weighted by inverse probability weights. Robust standard errors clustered at the applicant's place/university of origin. 'p-value' presents the uncorrected p-values, while 'p-value (corrected)' presents the p-values corrected for multiple hypothesis testing.

TABLE B.2. Assistant 1

	Time spent (standardized)		Last page visited		Proportion of questions filled		Proportion of pages visited	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Total effect								
AA	-0.139***	-0.140***	0.006	0.004	-0.001	-0.002	-0.000	-0.001
	(0.039)	(0.039)	(0.018)	(0.018)	(0.015)	(0.015)	(0.015)	(0.015)
Female	-0.005	-0.012	-0.056**	-0.060***	-0.050**	-0.056***	-0.048**	-0.054**
	(0.050)	(0.048)	(0.022)	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)
AA * Female	0.153***	0.153**	0.034+	0.035+	0.032+	0.033+	0.029	0.030
	(0.058)	(0.060)	(0.023)	(0.023)	(0.022)	(0.021)	(0.022)	(0.022)
Constant	0.000	0.037	0.384***	0.349***	0.400***	0.399***	0.423***	0.419***
	(0.040)	(0.136)	(0.020)	(0.045)	(0.019)	(0.045)	(0.020)	(0.045)
Observations	2,217	2,217	2,217	2,217	2,217	2,217	2,217	2,217
R-squared	0.004	0.009	0.003	0.017	0.002	0.018	0.002	0.019
B. Intensive margin effect								
AA	-0.228***	-0.227***	0.013	0.011	-0.001	-0.001	0.002	0.002
	(0.065)	(0.064)	(0.031)	(0.031)	(0.023)	(0.023)	(0.022)	(0.022)
Female	0.004	0.002	-0.093***	-0.093***	-0.079***	-0.079***	-0.072***	-0.072***
	(0.075)	(0.074)	(0.034)	(0.032)	(0.027)	(0.026)	(0.026)	(0.025)
AA * Female	0.240***	0.237**	0.048	0.050	0.044+	0.044+	0.035	0.035
	(0.090)	(0.092)	(0.037)	(0.037)	(0.029)	(0.029)	(0.026)	(0.026)
Constant	0.002	0.021	0.766***	0.589***	0.797***	0.694***	0.845***	0.726***
	(0.053)	(0.183)	(0.020)	(0.051)	(0.014)	(0.038)	(0.015)	(0.033)
Observations	1,098	1,098	1,098	1,098	1,098	1,098	1,098	1,098
R-squared	0.010	0.011	0.009	0.018	0.009	0.016	0.009	0.019
Other controls	No	Yes	No	Yes	No	Yes	No	Yes

Note: OLS regression results for Assistant 1. Cols (1), (3), (5) and (7) report the results without controls, while cols (2), (4), (6) and (8) report the results with controls. The control variables include age, a dummy for master's degree, a dummy for Bogota and a dummy for Coca region. The estimates in the second panel (intensive margin) are weighted by inverse probability weights. Robust standard errors clustered at the applicant's place/university of origin are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$, + $p<0.15$

TABLE B.3. Assistant 2

	Time spent (standardized)		Last page visited		Proportion of questions filled		Proportion of pages visited	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Total effect								
AA	-0.087***	-0.079**	-0.043***	-0.037**	-0.032**	-0.026*	-0.034**	-0.028*
	(0.032)	(0.034)	(0.016)	(0.017)	(0.014)	(0.014)	(0.016)	(0.016)
Female	-0.078**	-0.036	-0.058***	-0.033*	-0.046***	-0.023	-0.053***	-0.029+
	(0.034)	(0.038)	(0.017)	(0.018)	(0.015)	(0.017)	(0.016)	(0.018)
AA * Female	0.145***	0.120**	0.075***	0.060**	0.057**	0.042*	0.065***	0.050**
	(0.052)	(0.056)	(0.025)	(0.026)	(0.022)	(0.023)	(0.024)	(0.024)
Constant	0.021	0.410*	0.479***	0.866***	0.451***	0.795***	0.479***	0.869***
	(0.055)	(0.232)	(0.034)	(0.104)	(0.031)	(0.099)	(0.034)	(0.106)
Observations	2,191	2,152	2,191	2,152	2,191	2,152	2,191	2,152
R-squared	0.001	0.016	0.002	0.019	0.001	0.019	0.002	0.019
B. Intensive margin effect								
AA	-0.169**	-0.171***	-0.046**	-0.047**	-0.023+	-0.023+	-0.028	-0.028
	(0.066)	(0.063)	(0.022)	(0.022)	(0.015)	(0.015)	(0.021)	(0.020)
Female	-0.022	-0.037	-0.029	-0.029	-0.009	-0.010	-0.019	-0.020
	(0.073)	(0.068)	(0.024)	(0.024)	(0.017)	(0.018)	(0.026)	(0.026)
AA * Female	0.224***	0.234***	0.066***	0.064***	0.030**	0.029**	0.044**	0.042**
	(0.079)	(0.074)	(0.019)	(0.018)	(0.014)	(0.013)	(0.018)	(0.018)
Constant	0.013	-0.490	0.956***	1.244***	0.902***	1.115***	0.957***	1.248***
	(0.030)	(0.425)	(0.014)	(0.070)	(0.010)	(0.053)	(0.013)	(0.058)
Observations	1,028	1,028	1,028	1,028	1,028	1,028	1,028	1,028
R-squared	0.005	0.023	0.005	0.019	0.003	0.019	0.003	0.018
Other controls	No	Yes	No	Yes	No	Yes	No	Yes

Note: OLS regression results for Assistant 2. Cols (1), (3), (5) and (7) report the results without controls, while cols (2), (4), (6) and (8) report the results with controls. The control variables include age, dummy for master's degree, relative grade, risk preference, time preference, CRT score and the big five personality traits. The estimates in the second panel (intensive margin) are weighted by inverse probability weights. Robust standard errors clustered at the applicant's place/university of origin are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1, + p<0.15

Appendix C: Sentiment Analysis

TABLE C.1. Sentiment Analysis (Assistant 1)

	Valence score			Arousal score			Dominance score		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Total Effects									
AA	-0.048	-0.044	-0.020	-0.049	-0.045	-0.021	-0.047	-0.043	-0.019
p-value	(0.165)	(0.178)	(0.217)	(0.156)	(0.167)	(0.210)	(0.177)	(0.191)	(0.267)
p-value (corrected)	(0.264)	(0.287)	(0.324)	(0.259)	(0.274)	(0.314)	(0.275)	(0.297)	(0.374)
Female	-0.101	-0.125	-0.039	-0.103	-0.126	-0.041	-0.099	-0.123	-0.037
p-value	(0.017)	(0.001)	(0.031)	(0.014)	(0.001)	(0.022)	(0.017)	(0.001)	(0.061)
p-value (corrected)	(0.084)	(0.023)	(0.117)	(0.077)	(0.019)	(0.102)	(0.087)	(0.021)	(0.150)
AA * Female	0.112	0.108	0.04	0.116	0.112	0.043	0.107	0.103	0.034
p-value	(0.052)	(0.045)	(0.032)	(0.044)	(0.036)	(0.029)	(0.066)	(0.057)	(0.086)
p-value (corrected)	(0.140)	(0.131)	(0.106)	(0.127)	(0.119)	(0.114)	(0.162)	(0.146)	(0.186)
Constant	-0.000	0.284	-0.533	-0.000	0.287	-0.532	0.000	0.292	-0.526
	(1.000)	(0.106)	(0.000)	(1.000)	(0.112)	(0.000)	(1.000)	(0.104)	(0.000)
Observations	2,217	2,217	2,217	2,217	2,217	2,217	2,217	2,217	2,217
R-squared	0.001	0.024	0.937	0.002	0.024	0.938	0.001	0.025	0.939
B. Intensive margin effect									
AA	-0.087	-0.078	-0.031	-0.090	-0.081	-0.033	-0.086	-0.076	-0.029
p-value	(0.206)	(0.225)	(0.259)	(0.195)	(0.209)	(0.230)	(0.221)	(0.242)	(0.313)
p-value (corrected)	(0.292)	(0.309)	(0.349)	(0.284)	(0.296)	(0.319)	(0.309)	(0.323)	(0.400)
Female	-0.155	-0.183	-0.072	-0.158	-0.186	-0.075	-0.150	-0.178	-0.067
p-value	(0.018)	(0.004)	(0.018)	(0.013)	(0.003)	(0.011)	(0.020)	-0.005	(0.044)
p-value (corrected)	(0.075)	(0.031)	(0.074)	(0.064)	(0.024)	(0.061)	(0.078)	(0.034)	(0.117)
AA * Female	0.184	0.176	0.073	0.190	0.182	0.079	0.174	0.166	0.063
p-value	(0.067)	(0.057)	(0.030)	(0.057)	(0.045)	(0.023)	(0.086)	(0.074)	(0.079)
p-value (corrected)	(0.144)	(0.134)	(0.085)	(0.134)	(0.120)	(0.080)	(0.172)	(0.162)	(0.157)
Constant	-0.006	0.381	-0.897	-0.005	0.389	-0.895	-0.007	0.395	-0.883
p-value	(0.943)	(0.136)	(0.000)	(0.953)	(0.140)	(0.000)	(0.938)	(0.130)	(0.000)
Observations	1,098	1,098	1,098	1,098	1,098	1,098	1,098	1,098	1,098
R-squared	0.003	0.030	0.911	0.003	0.031	0.913	0.003	0.031	0.914
Other controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Statement length	No	No	Yes	No	No	Yes	No	No	Yes

Note: OLS regression results of the sentiment analysis on the statement of motivation (SoM) from Assistant 1 are reported. Cols (1), (4) and (7) report the results without controls, while cols (2), (5) and (8) report the results with controls. The control variables include age, a dummy for master's degree, a dummy for Bogota and a dummy for Coca region. Cols (3), (6) and (9) further includes the length (number of words) of the SoM. The estimates in the second panel (intensive margin) are weighted by inverse probability weights. Robust standard errors clustered at the applicant's place/university of origin are reported in parentheses. 'p-value' presents the uncorrected p-values, while 'p-value (corrected)' presents the p-values corrected for multiple hypothesis testing.

Table D.1. Effect of AA on Additional Outcomes (Assistant 2)

	Test score		Typing accuracy	
VARIABLES	(1)	(2)	(3)	(4)
A. Total Effects				
AA	-0.028	-0.025	-0.062	-0.048
p-value	(0.008)	(0.020)	(0.046)	(0.121)
p-value (corrected)	(0.083)	(0.130)	(0.172)	(0.266)
Female	-0.050	-0.028	-0.103	-0.054
p-value	(0.000)	(0.026)	(0.002)	(0.135)
p-value (corrected)	(0.016)	(0.133)	(0.045)	(0.290)
AA * Female	0.043	0.034	0.122	0.089
p-value	(0.010)	(0.053)	(0.011)	(0.067)
p-value (corrected)	(0.093)	(0.194)	(0.081)	(0.199)
Constant	0.349	0.614	0.025	0.798
p-value	(0.000)	(0.000)	(0.713)	(0.000)
Observations	2,191	2,152	2,191	2,152
R-squared	0.003	0.028	0.001	0.019
B. Intensive margin effect				
AA	-0.024	-0.025	-0.102	-0.102
p-value	(0.030)	(0.015)	(0.335)	(0.311)
p-value (corrected)	(0.077)	(0.049)	(0.432)	(0.423)
Female	-0.038	-0.027	-0.077	-0.081
p-value	(0.000)	(0.007)	(0.527)	(0.507)
p-value (corrected)	(0.008)	(0.045)	(0.653)	(0.645)
AA * Female	0.024	0.023	0.171	0.161
p-value	(0.046)	(0.045)	(0.063)	(0.071)
p-value (corrected)	(0.114)	(0.123)	(0.173)	(0.185)
Constant	0.694	0.881	-0.016	1.348
p-value	(0.000)	(0.000)	(0.799)	(0.000)
Observations	1,028	1,028	1,028	1,028
R-squared	0.009	0.056	0.002	0.017
Other controls	No	Yes	No	Yes

Note: OLS regression results for additional outcomes considering the Assistant 2 experiment are presented. The outcome in cols (1)-(2) is the equally-weighted average of the proportions of correct answers in probability test and reading-comprehension test. Typing accuracy in cols (3)-(4) is the negative of the average of two standardized Levenshtein distances corresponding to two typing exercises. In each typing exercise, we calculate the Levenshtein distance between the correct paragraph that is given to the applicant and the paragraph that the applicant has actually typed. The mean and standard deviation of the males in the control group are used to calculate the z-scores. Cols (1) and (3) report the results without controls, while cols (2) and (4) report the results with controls. The control variables include age, dummy for master's degree, relative grade, risk preference, time preference, CRT score and the big five personality traits.The estimates in the second panel (intensive margin) are weighted by inverse probability weights. Robust standard errors clustered at the applicant's place/university of origin are reported in parentheses. *p-value* presents the uncorrected p-values, while *p-value (corrected)* presents the p-values corrected for multiple hypothesis testing.

Appendix D: Additional Outcomes

Appendix E: Robustness check specifications

Table E.1. Assistant Pooled - Robustness Analysis with Alternative Models

	Time spent (hours) *Tobit model*		Last page visited *Probit model*		Proportion of questions filled *Fractional Probit model*		Proportion of pages visited *Fractional Probit model*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AA	-10.004***	-9.972***	-0.050	-0.050	-0.032	-0.031	-0.034	-0.032
	(3.397)	(3.558)	(0.041)	(0.039)	(0.034)	(0.034)	(0.036)	(0.036)
Female	-4.581	-4.819	-0.150***	-0.152***	-0.112***	-0.115***	-0.116***	-0.119***
	(4.257)	(4.358)	(0.036)	(0.037)	(0.033)	(0.034)	(0.036)	(0.036)
AA * Female	12.657**	12.269**	0.144***	0.141***	0.098**	0.094**	0.102**	0.098**
	(5.762)	(6.085)	(0.050)	(0.049)	(0.046)	(0.045)	(0.051)	(0.049)
Constant	-3.687	26.315	-0.278***	0.016	-0.255***	0.058	-0.188***	0.133
	(13.741)	(26.642)	(0.054)	(0.147)	(0.051)	(0.133)	(0.054)	(0.137)
Observations	4,480	4,480	4,408	4,408	4,480	4,480	4,480	4,480
Other controls	No	Yes	No	Yes	No	Yes	No	Yes

Note: Coefficients from alternative non-linear models estimating total effect using pooled data from Assistant 1 and Assistant 2 are reported. All regressions models include a dummy for Assistant 2. Cols (1), (3), (5) and (7) report the results without controls, while cols (2), (4), (6) and (8) report the results with controls. The control variables include the applicant's age and whether the applicant holds a master's degree. Robust standard errors clustered at the applicant's place/university of origin are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$, + $p<0.15$

TABLE E.2. Assistant 1 - Robustness Analysis with Alternative Models

	Time spent (hours) *Tobit model*		Last page visited *Probit model*		Proportion of questions filled *Fractional Probit model*		Proportion of pages visited *Fractional Probit model*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AA	-16.965***	-17.029***	0.015	0.012	-0.004	-0.006	-0.001	-0.003
	(6.351)	(6.519)	(0.046)	(0.047)	(0.039)	(0.040)	(0.038)	(0.040)
Female	-7.826	-10.021	-0.150**	-0.165***	-0.133**	-0.149***	-0.124**	-0.141**
	(9.859)	(9.722)	(0.060)	(0.059)	(0.056)	(0.055)	(0.056)	(0.055)
AA * Female	21.017*	20.853*	0.092+	0.094+	0.086+	0.088+	0.076	0.078
	(11.290)	(11.909)	(0.062)	(0.063)	(0.057)	(0.058)	(0.056)	(0.057)
Constant	-31.967***	171.708***	-0.296***	-0.390***	-0.254***	-0.254**	-0.193***	-0.204*
	(8.814)	(3.548)	(0.054)	(0.121)	(0.048)	(0.120)	(0.051)	(0.117)
Observations	2,217	2,217	2,217	2,217	2,217	2,217	2,217	2,217
Other controls	No	Yes	No	Yes	No	Yes	No	Yes

Note: Coefficients from alternative non-linear models estimating total effect using pooled data from Assistant 1 are reported. All regressions models include a dummy for Assistant 2. Cols (1), (3), (5) and (7) report the results without controls, while cols (2), (4), (6) and (8) report the results with controls. The control variables include age, a dummy for master's degree, a dummy for Bogota and a dummy for Coca region. Robust standard errors clustered at the applicant's place/university of origin are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$, + $p<0.15$

TABLE E.3. Assistant 2: Robustness Analysis with Alternative Models

	Time spent (hours) *Tobit model*		Last page visited *Probit model*		Proportion of questions filled *Fractional Probit model*		Proportion of pages visited *Fractional Probit model*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AA	-0.048**	-0.041**	-0.108***	-0.094**	-0.057	-0.040	-0.063	-0.044
	(0.019)	(0.020)	(0.041)	(0.042)	(0.045)	(0.048)	(0.049)	(0.051)
Female	-0.051**	-0.020	-0.147***	-0.085*	-0.091**	-0.034	-0.107**	-0.047
	(0.023)	(0.024)	(0.042)	(0.046)	(0.045)	(0.049)	(0.050)	(0.055)
AA * Female	0.081**	0.062*	0.190***	0.153**	0.106+	0.069	0.124+	0.085
	(0.032)	(0.035)	(0.063)	(0.066)	(0.069)	(0.069)	(0.076)	(0.075)
Constant	0.040	0.405***	-0.053	0.964***	-0.152+	0.778***	-0.084	0.952***
	(0.054)	(0.140)	(0.085)	(0.265)	(0.096)	(0.246)	(0.104)	(0.264)
Observations	2,191	2,152	2,191	2,152	2,263	2,219	2,263	2,219
Other controls	No	Yes	No	Yes	No	Yes	No	Yes

Note: Coefficients from alternative non-linear models estimating total effect using pooled data from Assistant 1 are reported. All regressions models include a dummy for Assistant 2. Cols (1), (3), (5) and (7) report the results without controls, while cols (2), (4), (6) and (8) report the results with controls. The control variables include age, dummy for master's degree, relative grade, risk preference, time preference, CRT score and the big five personality traits. Robust standard errors clustered at the applicant's place/university of origin are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1, + p<0.15

TABLE E.4. Sentiment Analysis (Assistant 1) using Tobit Model

	Valence Score			Arousal score			Dominance score		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AA	-3.508	-3.293	-1.361	-2.526	-2.370	-1.051	-3.478	-3.234	-1.279
	(4.832)	(4.762)	(1.802)	(3.352)	(3.292)	(1.292)	(4.902)	(4.814)	(1.897)
Female	-17.138**	-20.411***	-5.493***	-11.973**	-14.255***	-3.928***	-17.076**	-20.414***	-5.318***
	(8.234)	(7.864)	(1.864)	(5.631)	(5.369)	(1.222)	(8.175)	(7.788)	(2.022)
AA * Female	14.529*	14.262+	4.355**	10.308*	10.123*	3.301**	14.163+	13.873+	3.796*
	(8.790)	(8.730)	(1.901)	(6.010)	(5.939)	(1.330)	(8.831)	(8.724)	(2.011)
Constant	-28.987***	130.635***	28.053***	-20.255***	-3.046	-20.344***	-29.177***	-3.639	-28.573***
	(6.257)	(6.264)	(2.034)	(4.836)	(4.643)	(1.296)	(6.253)	(6.602)	(1.884)
Observations	2,217	2,217	2,217	2,217	2,217	2,217	2,217	2,217	2,217
Other controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Statement length control	No	No	Yes	No	No	Yes	No	No	Yes

Note: Coefficients from Tobit models for the sentiment analysis on the statement of motivation (SoM) from Assistant 1 are reported. Cols (1), (4) and (7) report the results without controls, while cols (2), (5) and (8) report the results with controls. The control variables include age, a dummy for master's degree, a dummy for Bogota and a dummy for Coca region. Cols (3), (6) and (9) further includes the length (number of words) of the SoM. Robust standard errors clustered at the applicant's place/university of origin are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$, + $p<0.15$

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