Discrimination, Rejection, and Job Search*

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ABSTRACT

We investigate how candidates' willingness to apply responds to (potential) discrimination and rejection using a simulated labor market. Past work has shown that "blinding" job applications reduces discrimination and increases the rate at which women are hired. Our study asks, how do blinding interventions impact the supply of candidates? Participants in our large online experiment are assigned to the role of either a recruiter or a candidate for a technical coding task. Candidates provide their willingness to apply for the opportunity with a non-blind resume that provides a coarse signal of their skills alongside gender and age, or a blind resume that hides the demographic information. We find that blinding applications increases the rate at which counter-stereotypical candidates apply, revealing an important channel through which blinding interventions can broaden and diversify the pool of talent. Our study goes beyond initial applications to explore the downstream effects of blinding in markets where candidates receive feedback. We ask whether rejections resulting from a blind process have a different impact than non-blind rejections. The effect could go either way: potential discrimination having a particularly discouraging effect on future application behavior, or a blind rejection instead being a stronger signal of quality and therefore inducing greater deterrence. We find support for the latter channel. Blind rejections have a larger impact on future applications than non-blind rejections, particularly for women. As a result, while blinding initially reduces age and gender gaps in willingness to apply, the supply-side benefits of blinding are more muted after a rejection. This causal evidence on the net effects of blinding advances our understanding of a practice that is gaining popularity in the field.

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1 Introduction

Nearly 25 years ago, Goldin and Rouse (2000) presented evidence on the impact of "blinding" a hiring process. Using data on symphony orchestras, they showed that hiding musician gender from evaluators – by having musicians audition behind a curtain – significantly increased the rate at which female musicians were selected. In the years since then, blind recruitment and hiring processes have gained traction as an important tool to increase organizational diversity. In a survey of more than 800 Human Resource professionals, more than half were familiar with blinding policies and approximately 20% reported that their organization used blinding in their recruitment (Fath and Zhu, 2021).

The case for blinding has centered on the demand-side of the labor market. By removing demographic information from applications or resumes, recruiters prevent themselves from discriminating on the basis of these characteristics. In this paper, we explore the impacts of blinding on the supply side of the market. Does blinding a hiring process grow and/or diversify the pool of qualified candidates that apply? That is, do more female musicians try out for the orchestra when they know the audition will take place behind a curtain? In the case that a female musician is rejected after her audition, does being rejected based on a blind audition discourage her more or less from applying again in the future compared to a non-blind rejection? How do candidates that would likely benefit from stereotypes respond to a blind hiring process?

We explore these questions using a large, controlled experiment in a simulated labor market on Prolific. We elicit evaluations of candidates from a sample of "recruiters," allowing us to measure discrimination. We pair these decisions with data from a large sample of "candidates," allowing us to observe detailed information on the qualifications and decisions of all potential applicants. Together, we are able to study how both the demand for and supply of candidates is shaped by blinding the evaluation process.

In the recruiter survey, recruiters are incentivized to hire candidates that they believe performed well on a 10-question coding skills test. We randomize recruiters into one of two regimes: evaluating candidates with blind resumes or evaluating candidates with non-blind resumes. They evaluate five different candidates under their assigned regime. All resumes contain information on the educational attainment of the candidate, the preferred field of study, and a sample performance on the coding skills test. In the non-blind regime, the resume also includes gender and age, while the blind resume excludes this information. Recruiters see candidates who are drawn at random from the universe of possible candidates in our study, allowing us to study evaluation decisions absent candidate selection effects. By comparing evaluations by age, gender, and regime, conditional on other resume characteristics, we can quantify the extent of discrimination. Our results reveal that, in the non-blind treatment, recruiters are significantly less likely to hire women and older candidates compared to other candidates with the same resume.

In the candidate survey, participants first take a coding skills test. Then, they provide their willingness to apply for an opportunity related to those skills, either with a blind resume or with a non-blind resume. After they make this decision, we elicit their willingness to apply under the other regime. These decisions are incentivized, as payoffs depend not only on their willingness to apply but also on recruiters' willingness to hire someone with their resume.[1] Again, all resumes contain information on a candidate's educational attainment, preferred field of study, and a sample performance on the coding skills test. In the non-blind regime, the resume also includes their gender and age. This enables us to measure the causal effect of blind resumes on the application behavior of candidates.

We find that blinding has a significant impact on the supply of candidates. On average, women are significantly less likely to apply than men with the same resume when the hiring process is non-blind. Blinding significantly reduces this gender gap. While men are equally likely to apply independent of whether the hiring process is blind or not, women are significantly more willing to apply when the process is blind. We also find that older individuals are less likely to apply in the non-blind regime than younger individuals with the same characteristics. Blinding directionally reduces this gap, but not significantly so in the initial application, in part because both younger and older individuals are more willing to apply under a blind hiring process. Importantly, we observe that demand for blinding is significantly greater among more talented candidates, that is, candidates who perform better on the skills test. In sum, blinding has significant, meaningful impacts on the supply of talent. A blind hiring process increases the overall size, average talent, and gender diversity of the applicant pool.

Because we have data on both sides of the market, we can examine market outcomes under

[1] Hired candidates are not required to do additional tasks or work; they simply receive higher payoffs.

both a blind and non-blind regime. We find that the pool of candidates hired in the blind market (relative to the non-blind market) is of no worse skill in expectation and has a weakly greater representation of both women and older individuals. Importantly, this results not only from a reduction in discrimination but also from an increase in the supply of talented candidates. In our setting, the benefits of a blind hiring process in terms of productivity and representation are estimated to be larger in a tighter labor market, where the number of candidates hired is small relative to the pool of applicants. Our results point to the importance of considering the supply-side of the market when designing hiring processes.

Our experiment then explores how candidate behavior evolves after a rejection. After their initial application decisions, all candidates in our pool receive (truthful) information that a given recruiter would have chosen **not** to hire them. We randomize whether this rejection was based on a blind resume or a non-blind resume. We ask candidates what they attribute this rejection to (gender, age, education, skills, etc.), we explore how they revise their likelihood of being hired both under blind and non-blind regimes, and then we elicit their incentivized willingness to apply to a new opportunity under a blind or non-blind regime.

As expected, rejection discourages future applications. After rejection, individuals report feeling less qualified for the opportunity and are significantly less willing to apply for future opportunities. Importantly, we observe significant heterogeneity in the extent of discouragement according to rejection type. Rejection resulting from a blind hiring process has a significantly larger impact on future application behavior. This effect is driven entirely by women and older individuals. While young men's willingness to apply falls after rejection, the drop is similar for blind and non-blind rejections. On the other hand, the application rates of women and older individuals fall significantly more after a blind rejection than a non-blind rejection. In sum, rejections that could be rationalized by recruiter discrimination have significantly less impact on future application behavior than rejections resulting from a blind hiring process. In addition, candidates are more likely to say that the recruiter's decision was fair and they report less disappointment when their application was rejected with a blind resume.

We show that women and older individuals continue to prefer blind to non-blind applications compared to young men under both rejection regimes. But rejection does have a significant impact on demand for blinding in future applications. After rejection on a non-blind resume, demand for blinding in future applications increases. This is true independent of a candidate's age or gender. This is consistent with candidates believing that their demographic information may have contributed to their rejection, leading them to prefer blind applications to non-blind applications going forward. But what if the rejection resulted from a blind resume? In this case, it matters whether the candidate believes the stereotypes work for or against them. After being rejected on a blind resume, men reveal a preference for **non-blind** applications going forward and younger individuals become indifferent between blind and non-blind applications. Candidates who think the stereotype benefits them decrease their relative demand for blinding after rejection on a blind resume. But, for candidates that believe the stereotype works against them, a blind rejection does not significantly decrease their relative demand for blind hiring processes moving forward.

Together our results suggest important impacts of blind hiring processes on candidate behavior. Blind hiring processes initially draw in more candidates, particularly candidates that belong to stereotyped groups (in our setting, women and older individuals). Not surprisingly, rejection discourages candidates and decreases their willingness to apply going forward. On average, these discouragement effects are larger after rejection on a blind application; this is driven by women. Blind rejections lead to twice as large of reduction in applications from women than non-blind rejections. Thus, while blind hiring processes lead to smaller gender gaps in willingness to apply ex ante, gender gaps are similar under blind and non-blind processes following a rejection. Despite the fact that blind rejections have a larger negative impact on future application behavior, they do not decrease the demand for blinding among stereotyped groups. Women and older individuals continue to prefer blind processes to non-blind processes even after being rejected via a blind process.

Our paper contributes to a growing literature that explores how candidates anticipate and respond to the possibility of discrimination. Similar to the main findings from Goldin and Rouse (2000), natural and field experiments find that blind hiring policies reduce recruiter discrimination against counter-stereotypical candidates (Åslund and Skans, 2012; Krause et al., 2012; Neumark, 2024). Recent studies suggest that negatively stereotyped candidates may prefer blind hiring processes due to concerns about the possibility of discrimination. For instance, Alston (2019) finds evidence in an online experiment that women anticipate gender discrimination against them in male-typed tasks and are, on average, willing to pay to remove their gender from their task-specific resume. Similarly, Charness et al. (2020) report that women often choose not to reveal their gender when applying for stereotypical male tasks, to avoid recruiter bias. Recent surges in the use of AI in hiring have also sparked research into how blind algorthmic hiring impacts application behavior, with Avery et al. (2024) finding that blinded AI processes increase the proportion of female candidates that complete the application for a male-dominated tech job, but Ruebeck (2024) finding more muted effects. More broadly, research has found that negatively stereotyped candidates prefer to conceal or downplay aspects of their identity in response to expected discrimination, anticipating that removing this information will lead to a higher probability of being hired or to higher expected earnings (Kang et al., 2016; Kudashvili and Lergetporer, 2022; Aksoy et al., 2023). Researchers have also explored the labor market consequences of name changes among immigrants, showing positive labor market returns to this form of assimilation (Biavaschi et al., 2017; Arai and Skogman Thoursie, 2009). Concealing identity has been studied in market interactions, with Zussman (2013) showing that Arab sellers strategically omit their name from listings in an online Israeli car market in anticipation of discrimination and Kudashvili and Lergetporer (2022) finding that Armenians, an ethnic minority in Georgia, choose to misrepresent their names to mask their ethnicity in a trust game played with out-group members. There is also evidence that the psychological cost associated with experienced discrimination further motivates candidates to avoid non-blind applications (Ruebeck, 2024; Ridley, 2023).

Of course, while some candidates anticipate discrimination, others may expect it to work in their favor. This can be due to where their true productivity lies in relation to the prior of the recruiter (Phelps, 1972; Arrow et al., 1973; Aigner and Cain, 1977) or, more generally, to favorable stereotypes or affirmative action. Indeed, Kline et al. (2022) find significant heterogeneity in the extent of gender and race discrimination among a large sample of US firms, with some firms demonstrating a preference for members of under-represented groups. For instance, Koutout (2022) finds that men who think that recruiters hold favorable stereotypes prefer to reveal their gender, and Behaghel et al. (2015) shows that under-represented or counter-stereotypical candidates can increase their chances of being hired by revealing their identity if hiring firms apply affirmative action policies.

Researchers have also studied how perceived discrimination impacts behavior at later stages of recruitment, from job search, to interview performance, to on-the-job performance. For instance, Glover (2024) shows that changes in beliefs about the distribution of recruiter discrimination can affect job search intensity and application quality of members of under-represented groups. Similarly, Goldsmith et al. (2004) find that perceived racial or ethnic discrimination during job search periods negatively impacts women's labor supply, while such perceptions have no significant effect on male labor supply. Similarly, Gagnon et al. (2022) show that women reduce labor supply on the intensive margin when informed that they are paid less than men for performing the same task. After securing an interview, anticipated discrimination on the basis of socioeconomic status has been found to negatively impact interview performance among low-income job-seekers in Brazil (Angeli et al., 2024). Once on the job, Glover et al. (2017) shows that minority grocery store employees perform worse when managed by more implicitly biased supervisors, while in an online experiment Ruebeck (2024) finds that employees who perceive discrimination show weaker performance and engagement in the work task. The negative impact of discrimination on worker performance has also been shown in other contexts, such as in sports (Parsons et al., 2011; Caselli et al., 2023) and education (Hill and Zhou, 2023).

Relative to this work, our contribution is to causally identify the impacts of the possibility of discrimination on willingness to apply, both before and after negative feedback. In addition to incentivized willingness to apply data, we collect an array of other measures on candidate beliefs and preferences, allowing us to unpack the factors that drive application decisions under both blind and non-blind hiring processes, across both positively and negatively stereotyped groups. We couple this candidate data with rich data on recruiter decision-making to speak to market-level effects. Furthermore, we observe dynamic responses to rejection. We can explore how discouragement and beliefs evolve after negative feedback, and we can compare these effects across blind and non-blind rejections. This allows us to speak to longer-term impacts of moving to blind hiring processes and contribute to an active literature that explores the role of biased beliefs in optimal job search strategies (Cooper and Kuhn, 2020; Santos-Pinto and de la Rosa, 2020; Mueller et al., 2021; He and Kircher, 2023). We show that blinding and rejection significantly impact the propensity of candidates to apply to jobs and, in-turn, receive feedback from employers under two regimes: when discrimination is or is not a possibility. Thus blinding may not only induce changes in the labor supply of stereotyped groups, but also increase the amount of objective rejection feedback candidates receive. Furthermore, we document how the choice of hiring process impacts candidate beliefs about hiring probabilities, experienced discouragement, and rationalizations of rejection.

Finally, we explore alternative explanations for demand for non-blind versus blind applications, beyond anticipated discrimination. Candidates might prefer non-blind resumes to screen out prejudiced employers, attempting to avoid interacting with a recruiter who would eventually discriminate against them, for instance during the job interview. Second, candidates may directly gain utility from revealing their identity, for instance via pride or honesty. Finally, these decisions may also relate to self-image. For instance, candidates may prefer non-blind resumes because they can attribute rejection to discrimination rather than to a lack of skills (Cooper and Kuhn, 2020; Heidhues et al., 2019), potentially allowing them to maintain more positive beliefs about their talents. Conversely, candidates may have a higher demand for blind resumes if they prefer to escape the competence-signaling problem (Bijkerk et al., 2021), that is if they prefer to be evaluated on their skills rather than potentially benefiting from "positive discrimination" or quota policies. Our detailed survey questions allow us to weigh these various factors, both within the context of our experimental environment and more broadly.

2 Experimental design

We conduct two large controlled experiments on Prolific in order to study recruiter and candidate behavior. In the section below, we first describe the Recruiter Study in detail. Then, we describe the Candidate Study. In the final section, we describe how these experiments are integrated in order to incentivize decisions and generate outcomes. Throughout the sections below, we use the term recruiter to refer to a Prolific participant who has been assigned to evaluate resumes and the term candidate to refer to a Prolific participant who has been assigned to assemble a resume and make application decisions. We frame these decisions in the context of a job opportunity.

2.1 Recruiter Study

The primary goal of the Recruiter Study is to measure the extent of discrimination in our setting by comparing evaluations across candidate gender and age.

2.1.1 The Technical Test

The main task for recruiters is to evaluate candidates based upon their technical skills related to coding and computer programming; for simplicity, we refer to this as the technical test. We tell recruiters that we have asked all candidates to complete a test that assesses their computer programming and coding skills. This test consists of 10 multiple-choice questions and must be completed within three minutes. We show recruiters the test to familiarize them with the assessment; the full test can be found in Appendix B.

2.1.2 Candidate Resumes

After viewing the test, recruiters are asked to evaluate a series of candidate resumes. Each recruiter is randomly assigned to either the Blind or Non-Blind treatment. They evaluate five resumes from their assigned treatment in sequence with no feedback between resumes. All resumes include information about a candidate's educational attainment (high school or less, bachelor's, or advanced degree) and self-reported favorite subject (humanities, social science, or STEM). They also include a small sample of their performance on the programming assessment; in particular, we randomly draw two questions from the test and show the candidate's total number of correct answers on those questions (0, 1 or 2 out of 2). In this way, the sample performance provides a noisy but informative signal of candidate ability, leaving room for potential belief-based discrimination.

The non-blind resumes also include the candidate's gender (man or woman) and age (under 45 years old or 45 years old and above). We use only two categories for age and gender to simplify our analysis and reduce the number of potential resumes for recruiters to consider.[2] We collect recruiter evaluations of all possible candidate resumes. Given the information presented on resumes, there are 27 possible resumes in the Blind treatment and 108 possible resumes in the Non-Blind treatment. Examples of resumes can be found in the Appendix C.

2.1.3 Evaluation Decisions

For each resume, recruiters are asked to decide how willing they would be to have their bonus payment depend upon that candidate's full performance on the 10-question technical test. We use

[2]Wonly collected non-blind evaluations of men and women in anticipation of statistical power limitations. The 45 year old threshold is close to the median age of the US workforce, 41.8 in 2022, according to BLS.

a multiple-price-list design in order to elicit willingness to hire at a variety of prices. In each row of the price list, the recruiter must decide whether they would prefer to "Hire" the candidate or not. In every row, the payoff to hiring the candidate is 50 cents for every question answered correctly by the candidate. The payoff to not hiring the candidate increases as the recruiter proceeds down the price list. The first row of the price list asks the recruiter whether they would rather "Hire" or instead receive $0.50 with certainty. In each row, this outside option increases by $0.50, up to $10.50 total. In this way, our design elicits hiring decisions across a series of different outside options, increasing in attractiveness. We refer to the highest price at which a recruiter is willing to "Hire" a given candidate as their willingness to hire that candidate.[3] Appendix Figure D1 provides an illustration of the full recruiter price list.

Observe that we include outside options that strictly dominate the expected payoff to hiring even the best candidate. The best possible performance on the test is a score of 10, leading to a payoff from hiring that candidate of $5. Approximately half of the rows in the price list offer outside options that exceed this amount. We do this for two reasons. First, we wanted to guarantee that even the best possible candidates faced likely rejection by many recruiters so that we could study responses to rejection among an unselected sample. Second, by including rows with a dominated option, we can screen for recruiter comprehension and attention (see Appendix E).

We incentivize recruiters' decisions. We inform participants that 10% of recruiters will be randomly selected to have their choices count for bonus payment. Selected recruiters are matched to a candidate with a resume identical to one of the five resumes they evaluated. The computer then randomly chooses a row from the price list they completed for that resume and implements the recruiter's choice for that specific row. In this way, each hiring decision is potentially payoff relevant for the recruiter.

Note that in our context recruiters have no direct interactions with candidates, regardless of whether they choose to hire them or not. This may limit the extent to which taste-based discrimination is relevant in our setting. However, while there is no interaction between recruiters and candidates, recruiters are aware that their hiring decisions may impact candidate payoffs, with

[3] We programmed the experiment to enforce monotonicity in recruiter decision-making. That is, once a recruiter switched from hire to not hire for a given candidate, the price-list auto-filled to not hiring that candidate for all remaining rows (which offer more attractive outside options). The recruiter could over-ride this autofill by clicking again on the price-list and selecting a new switch point.

hired candidates earning more in expectation.

2.1.4 Recruiter Beliefs

In addition to studying discrimination in evaluation decisions, we also ask recruiters directly about their beliefs of performance across different groups. Recruiters are presented with each possible resume characteristic and asked to guess the average test score of a member of that group. For instance, recruiters are asked to guess the average test score of candidates with a favorite subject of "STEM," etc. We do not incentivize these stated beliefs, prioritizing simplicity. This allows us to document believed differences in performance across age and gender and to also benchmark these differences relative to differences across other characteristics (favorite subject, education, sample performance). We elicit these beliefs at the beginning of the study, prior to resume evaluations.[4]

2.1.5 Economic Preferences and Demographics

In the final sections of the Recruiter Study, we collect basic demographic information and economic preferences from the recruiters. Using the methodology of the Falk et al. (2018) paper, we measure risk preferences, patience, and altruism, each on a $0 - 10$ scale. Finally, we ask recruiters their gender, their age, and their ethnicity, as well as their highest level of education and their favorite school subject. The Recruiter Study also contains comprehension questions, geared at ensuring recruiters understand the multiple price list elicitation, and an attention check that requires recruiters to provide an open answer response.

2.2 Candidate Study

The primary goal of the Candidate Study is to explore willingness to apply under blind and non-blind hiring processes. We incentivize decisions in the Candidate Study by offering a bonus payment based upon their response to one randomly-selected question from the survey, which we refer to as the "decision-that-counts." These incentives are described in more detail below.

[4] We faced a trade-off in the timing of this elicitation. Eliciting beliefs before resume decisions could potentially prime recruiters to make decisions more in line with their beliefs, while eliciting beliefs after could lead to beliefs being influenced by the particular set of resumes displayed. In pilot studies, we randomized the timing of this belief elicitation, observing no clear differences. Ultimately, we decided to elicit beliefs before to prioritize the collection of uncontaminated beliefs.

2.2.1 Resume Building

In the first part of the Candidate Study, we ask all candidates some basic questions about themselves that we can use to build a stylized resume. We ask them their gender (man, woman, non-binary or third gender, or prefer to self-describe), their age, their highest level of education, and their favorite school subject (humanities, social science, or STEM).[5] At this stage of the study, participants know they will be making application decisions as a candidate, but they are not explicitly told that these answers will appear on a resume.

2.2.2 Technical Test

We then introduce candidates to the technical test. Recall that the technical test consists of 10 multiple-choice questions that assess skills related to coding and computer programming. A full copy of the technical test is available in Appendix B. Candidates have three minutes to complete the test. Candidates are told they will earn a \$1 bonus payment if the decision-that-counts is one of the test questions and they answered it correctly.

Following the test, we ask candidates what they believe their score on the technical test was. If this question is selected as the decision-that-counts, they earn \$1 in bonus payment if they correctly guessed their score. Note that we do not inform candidates of their score on the technical test, increasing the likelihood that self-confidence plays a role in application decisions. In this way, our setting mirrors a setting in which applicants have only imperfect information about their qualifications for a position.

2.2.3 Initial Application Decisions

After completing the technical test, candidates learn about the application opportunities. We inform candidates about the Recruiter Study, explaining that previous Prolific participants evaluated candidates, acting as recruiters for a job opportunity. They are told that we showed them several example candidate resumes, and that for each candidate, recruiters had to decide how willing they would be to hire a candidate with that resume. We tell them, truthfully, that recruiters were more willing to hire candidates that they thought had strong technical test scores.

[5] Candidates who identify as non-binary/third gender or other are excluded from our final sample for analysis, as pre-registered.

Given this information, candidates must make decisions about how willing they are to submit an application to an opportunity. Candidates are told that if they choose to apply to an opportunity, they will be paired with a randomly-chosen recruiter who evaluated a resume that exactly matched their resume. If the selected recruiter chose to hire the candidate (in a randomly-selected row of the multiple price list), the candidate earns \$1 in additional pay.[6] If the recruiter did not choose to hire them, they earn \$0. We expect that candidates should be more willing to apply the more likely they believe it is that a recruiter would hire someone with their resume.

We are interested in their willingness to apply under both blind and non-blind recruitment processes. We choose to implement a within-subjects design, where each candidate is asked their willingness to apply under both a blind and non-blind process. We randomize the order in which these elicitations appear. Collecting within-subject data increases our statistical power, allowing us to speak more precisely to candidate demand for blind application processes.

For each application opportunity, candidates are first shown the resume that would be used for their application, either a Blind Resume that includes only their education, favorite subject, and sample performance or a Non-Blind Resume that also includes their gender and age (under 45, 45 or older). Note that for the sample performance, participants are aware that the resume will contain their performance on two randomly-selected questions from the technical test, but they are not informed about the exact realization. Therefore, their believed technical test score is relevant for their application decision, as it likely informs their beliefs about the sample performance score that will be shown (0, 1, or 2).

We use a multiple price list to elicit a continuous measure of willingness to apply. Each row of the price list has two options: "Apply" or "Do not apply". In each row, "Apply" generates the same payoff: \$1 only if they are hired by their matched recruiter. In the first row of the price list, they choose between applying and an outside option of receiving \$0.05 for sure. In each row, we increase the fixed payoff to the outside option of not applying, increasing it in \$0.05 increments up to \$1.25. Note that, similar to the recruiter price list, this candidate price list includes rows with a dominated option. The final 5 rows offer fixed payments of more than \$1, making it strictly payoff-maximizing to not apply. Again, this feature allows us to screen for attention and comprehension among participants, exactly in the moment at which they are completing one of the main measures

[6]Note that being hired does not involve completing any additional tasks.

of the experiment. Throughout this experiment, we define the candidate's "willingness to apply" as the largest outside option (payoff to not applying) at which the candidate still preferred to apply.[7]

Candidates assigned to see the Blind (Non-Blind) treatment first are shown their Blind (Non-Blind) Resume and make their willingness to apply decision. Then, they are shown their updated resume that adds (removes) their gender and age. They then make a willingness to apply decision for this new Non-Blind (Blind) Resume.

2.2.4 Pre-Rejection Perceptions

Following the willingness to apply decisions, we ask participants a series of questions about their perceptions of their blind and non-blind applications. First, we ask candidates their beliefs about the returns to blinding an application. In particular, we explain that we showed them two different versions of their resume and asked them which one they thought a recruiter would be more likely to hire. They answer on a 7-point response scale, ranging from much more likely to be hired with a resume that includes their age and gender to much more likely to be hired with a resume that does not include their age and gender. To understand how candidates perceive the overall likelihood of being hired, we ask them what they thought the overall percentage of candidates being hired with a Blind Resume was and what they thought the overall percentage of candidates being hired with a Non-Blind Resume was.

We then shift to a series of resume-specific beliefs. At this stage in the experiment, candidates are randomly-assigned to answer questions related to either their Blind or Non-Blind Resume. This is an across-subject randomization. We will refer to this randomly-assigned treatment as their "Rejection Type," as it is also the version of the resume that they will receive feedback on at the next stage of the study.[8]

For the selected resume type, they are asked how likely they believe it was that a recruiter hired someone with that exact resume. To better understand how candidates might interpret rejection, we ask candidates how disappointed or frustrated they would be if they were rejected based upon this resume (ranging from 0 to 10), how qualified they feel relative to other candidates (7-point

[7] As in the Recruiter Study, the experimental program enforces monotonicity. As soon as a candidate switches to not applying, the program autofills the remaining rows with the choice of not applying.

[8] At this stage, we do not tell candidates that they will receive feedback on this resume. Instead, we tell them: "We would now like you to focus on the version of your resume, which does (does not) include your age and gender. The questions below ask you about your choices for this version of your resume."

scale ranging from not at all qualified to extremely qualified), and their best guess for their sample performance shown on their resume (0, 1, or 2, incentivized with a $1 payment if they guess correctly and this is the decision-that-counts).

Finally, we ask candidates to imagine they were **hired** by the recruiter with their assigned resume. They are asked to allocate 100 points across the different features of their resume, indicating to which features they would attribute this outcome. For candidates assigned to consider the Blind Resume, this means deciding how much their education, favorite subject, and sample performance contributed to the recruiter's decision to hire them. For candidates assigned to consider the Non-Blind Resume, this means deciding how much their education, favorite subject, sample performance, age, and gender contributed to the recruiter's decision to hire them. Following these decisions, we ask candidates to then imagine they were **not hired** by the recruiter with their assigned resume. They are again asked to allocate 100 points across the different features of their resume, indicating to which features they would attribute this rejection.

2.2.5 Rejection

One important goal of the study is to understand how candidates respond to rejection in the labor market and to explore whether this response varies depending upon whether that rejection resulted from a blind or non-blind hiring process. In observational contexts, the researcher only observes rejection responses from a selected set of candidates, those who both chose to apply and yet were rejected. We construct a controlled environment in which we are able to provide negative feedback to all candidates, independent of their application decisions or application quality. This allows us to speak to responses to rejection absent selection effects.

To accomplish this, we rely on the fact that recruiters were offered many choices in which their outside option - the payoff to not hiring the candidate - strictly dominated the possible payoff to hiring the candidate. This means, for every possible resume, we observe many hiring decisions in which the candidate was not hired. We use this data to truthfully inform candidates about one particular evaluation decision.

We tell candidates: "Before you continue, we wanted to provide you with some feedback. This feedback is based on how one recruiter evaluated your resume. It is independent from the choices you submitted in the previous lists. This recruiter saw this resume: [insert either their Blind or

Non-Blind Resume, depending upon their randomly-assigned rejection type]. Given the choice they had, they chose NOT to hire you." This provides all candidates with imprecise negative feedback.

2.2.6 Post-Rejection Perceptions

Following the feedback, we ask candidates questions related to how they attribute this negative outcome. First, we ask them again what they believe their resume sample performance was, exploring whether they negatively revise their beliefs about their technical test score. Second, we ask them how fair they believe this rejection was on a 7-point scale, ranging from completely unfair to completely fair. Third, we ask them what they believe the likelihood is that another recruiter would choose to hire them with this same resume, exploring how they update their beliefs about the likelihood of being hired. Similarly, we ask them again about their beliefs about the overall likelihood of candidates in general being hired with blind and non-blind resumes in the study. Finally, we re-ask the questions about how disappointed or frustrated they feel given this rejection, how qualified they feel relative to other candidates, and their beliefs of how much each feature of their resume contributed to the negative outcome.

2.2.7 Post-Rejection Application Decisions

We explore how candidates' willingness to apply responds to rejection. We use the same multiple price list methodology to re-elicit their willingness to apply with a Blind and Non-Blind Resume. These resumes are identical to their pre-rejection resumes, and the decision structure is also the same as before. We explain that in the event that they choose to apply, they will be matched with a new randomly-selected recruiter to determine the outcome.

Candidates first provide their updated willingness to apply for the resume they received feedback on. That is, if they were randomly-assigned to receive a rejection based upon their Blind (Non-Blind) Resume, they first decide how willing they would be to apply again with a Blind (Non-Blind) Resume. After they complete that price list, they then provide their willingness to apply with the alternative resume. We therefore obtain within-subject comparisons of how willingness to apply changes after rejection, and in particular how a candidate's relative demand for a blind application changes after a rejection.

2.2.8 General Perceptions of Blind Hiring Processes

After a candidate has made all of their willingness to apply decisions, they proceed to the final portion of the survey which asks a variety of questions related to their perceptions of blind and non-blind hiring processes. We start with questions specific to our experiment. In four separate questions, we ask candidates their beliefs about whether men, women, individuals under 45 years old, and individuals 45 years old and above were more or less likely to be hired under a blind hiring process compared to a non-blind hiring process (5-point scale ranging from "Much More Likely" to "Much Less Likely").

We then ask candidates to think more broadly, beyond the context of our specific experiment. On a 7-point scale, we ask them how worried they are in general about facing discrimination in the job market on the basis of their gender and (separately) their age. We ask directly about their preferences for blind application processes, asking them, "In general, when you apply for jobs, would you prefer for recruiters to be able to see your demographic characteristics, such as your gender, age, and race, or would you prefer they not have access to this information in your application?" They respond on a 7-point scale ranging from "Strongly Prefer Recruiters Have Access to Demographics" to "Strongly Prefer They Do Not." We ask candidates to imagine they were hired for a position and ask whether they would prefer to have been hired under a blind or non-blind hiring process (5-point scale); similarly, we ask candidates to imagine they were rejected for a position and ask whether they would prefer to have been rejected under a blind or non-blind hiring process.

To unpack these preferences, we ask candidates to indicate their agreement (on a 5-point scale ranging from "Strongly Disagree" to "Strongly agree") with a set of statements about including their demographics on their application: they believe it will help them get an interview; they believe it supports diversity, equity, and inclusion in the workplace; it helps to filter out discriminatory employers; it shows a part of their identity that they are proud of; and it creates a doubt as to whether competence or identity drove a hiring decision. Finally, we ask them more broadly about their agreement (7-point scale) with a set of statements about blind hiring processes: blind hiring processes lead to a more diverse applicant pool, blind hiring processes lead employers to hire a more diverse workforce, blind hiring processes lead to a more productive workforce, and blind hiring processes should be standard policy for all employers.

This final part of the experiment also asks candidates about their race and ethnicity. We avoid asking this demographic question earlier as we want to avoid confusion as to what information does or does not appear on resumes within the study. We also elicit risk preferences using the Falk et al. (2018) 0-10 scale. And, we ask participants how difficult they found the instructions of the experiment (7-point scale ranging from "Very Easy to Understand" to "Very Difficult to Understand"). Note that the survey also includes an attention check which requires an open-text response and multiple comprehension questions that participants must answer correctly before they continue.

2.3 Implementation and Logistics

We ran the Recruiter Study in June 2024. As pre-registered, we posted our study to Prolific for 2,500 participants to complete. We pre-registered that this sample size corresponds to our unrestricted sample, that is, before eliminating participants who do not pass our pre-registered attention, understanding, coherence, and timing tests. We describe our sample restrictions in detail in Appendix E. We restricted participation to those users who had completed at least 100 studies with an approval rating of 95% or above. The study is advertised as approximately 15 minutes. In addition, we required users to complete the study using a computer rather than a mobile device to ensure that the instructions were clearly formatted.

Recruiters received \$3 for completing the study. In addition, 10% of recruiters are randomly selected for bonus payment. Selected recruiters are randomly matched to a candidate with a resume that is identical to one of the five resumes they evaluated. The computer then randomly chooses a row from the price list they completed for that resume and the recruiter's choice for that specific row is implemented. The recruiter earns \$0.50 for every question answered correctly by the matched candidate if they chose to hire in the selected row; if they chose not to hire in the given row, they receive the fixed payment for the row.

We ran the Candidate Study shortly after the Recruiter Study in June 2024. As pre-registered, we collected data from 4,000 Prolific participants using the same requirements on number of past studies, approval rate, and computer use as we implemented for the recruiter survey. This sample size corresponds to respondents before filtering according to our pre-registered sample restrictions. We pay a \$5 completion payment for a study that is advertised as 25 minutes. We use Prolific's built-in filters to collect a sample that is balanced on our key demographic variables. In particular, we impose that Prolific field candidate data as follows:

- 1,000 men, 45+;
- 1,000 men, under 45;
- 1,000 women, 45+;
- 1,000 women, under 45.

We incentivize candidates' willingness to apply, test performance and beliefs using the "decision-that-counts." At the end of the study, one decision made by each participant is randomly selected to serve as the "decision-that-counts" for bonus calculation. This decision is randomly chosen from all possible incentivized choices made throughout the study: each row of all four willingness to apply price lists, each of the questions on the technical test, and their belief of their performance on the technical test.

After applying our sample restrictions, we are left with a final sample of 1,217 recruiters and 2,488 candidates. We provide descriptive statistics of our final sample in Appendix Table A1 and a test of successful randomization in Appendix Table A2. In addition, the full experiment instructions for both the Recruiter Study and the Candidate Study, as well as figures illustrating the survey flows, can be found in Appendix F.

3 Hypotheses

In this section, we lay out our main research questions and explain which outcome measures we will use to address them.

3.1 Demand for Blind Applications

First, we investigate how a blind application process impacts application rates. We relate these decisions to candidate perceptions of recruiter discrimination. We expect that relative demand for blind applications varies by whether the candidate is likely to benefit from stereotypes (men, younger candidates) or not (women, older candidates). We hypothesize that candidates who expect recruiter discrimination against their type have a greater demand for blind resumes. These candidates are likely to expect greater chances of being hired if recruiters cannot observe individual characteristics, such as gender or age, that may lead to discrimination against them. Conversely, candidates who expect recruiters to favor their type (either due to preferences or beliefs) are likely to have a greater demand for non-blind resumes. These candidates are likely to want to signal their type to recruiters to increase their chances of being hired.

In addition, we investigate whether candidates are well-calibrated on the benefits of blinding. We can compare candidates' anticipated benefit of blinding, in terms of likelihood of being hired, to the observed benefit of blinding in the recruiter data. Past literature suggests that counter-stereotypical candidates may over-estimate the effect of blinding. Indeed, Alston (2019) finds that workers overestimate how much their gender affects their selection probability in a stereotypical male task, and Lepage et al. (2022) find that female students expect different returns from signaling their productivity through their grades, specifically because they anticipate labor market discrimination.

3.2 The Impact of Rejection on Willingness to Apply Again

Candidates often face rejections during job search. These rejections provide negative feedback about skills and relative qualifications, which can result in discouragement and lower job search intensity in order to avoid further negative feedback (Cooper and Kuhn, 2020; Bapna et al., 2021). Discouragement and negative feedback avoidance could contribute to the empirical finding that job seekers tend to reduce job search intensity as unemployment duration increases (Krueger and Mueller, 2011; Faberman and Kudlyak, 2019).

The second key contribution of this paper is to explore how job candidates react to rejection of their applications when recruiters can or cannot discriminate. In our study, we consider how a rejection impacts willingness to apply again in the future. Because of our controlled environment, we are able to observe responses to rejection among an unselected sample. We consider the impacts of rejection on willingness to apply to new opportunities and on relative demand for blind hiring processes. We consider how these impacts vary both by rejection type (based on a blind or non-blind resume) and candidate type (member of a negatively stereotyped group or not).

We hypothesize that, following rejection, candidates reduce their willingness to apply relative to before rejection. Indeed, rejection provides candidates with negative feedback, which can negatively affect their beliefs about their own performance and their beliefs about the overall hiring rate of recruiters, reducing the expected return from applying. This effect is expected regardless of whether the rejection was for a blind or non-blind resume.

More interestingly, we explore whether rejection based on a blind resume deters candidates more from applying again compared to rejection for a non-blind resume. When rejection occurs for a blind resume, candidates may attribute it more directly to their skills or qualifications rather than discrimination, leading to a greater downward adjustment in their beliefs about their skills and their willingness to apply going forward (regardless of whether that future application is blind or not). In line with previous results suggesting asymmetric updating of beliefs in line with stereotypes, this effect on candidates beliefs may be stronger for counter-stereotypical candidates (Niederle and Vesterlund, 2007; Coffman, 2014; Coffman et al., 2024).

In contrast, candidates rejected with a non-blind resume may be more likely to attribute rejection to discrimination. Attributing rejection to discrimination instead of lower skills or attractiveness could reduce discouragement compared to rejection on a blind resume, for instance by protecting job seekers' self-image after the rejection of an application. While this may lead them to decrease their beliefs about the likelihood of being hired given expected discrimination, we expect that a non-blind rejection has a smaller impact on their beliefs about their own qualifications. How might these two forces impact willingness to apply?

If candidates adjust their beliefs about their own abilities less after a non-blind rejection than a blind rejection, then we expect that they should be more willing to apply again – with a blind resume – than candidates who were rejected blind. However, because a non-blind rejection may increase perceived discrimination, we expect that it may increase relative demand for blinding. That is, willingness to apply with a non-blind resume should drop more relative to willingness to apply with a blind resume, especially among counter-stereotypical candidates who are more likely to face discrimination.[9]

[9] This would be in line with previous field evidence on discrimination and discouragement. For instance, Glover (2024) shows that changes in beliefs about the distribution of recruiter discrimination can affect job search intensity and application quality of minorities. Similarly, Goldsmith et al. (2004) find that perceived racial or ethnic discrimination during job search periods negatively impacts women's labor supply, while such perceptions have no significant effect on male labor supply.

3.3 Net effects

The third and final objective of this paper is to investigate the total effect of moving from a non-blind to a blind hiring process, factoring in not only impacts on the demand-side (recruiters) but also on the supply- side (candidates). How does a blind hiring process change the applicant pool and the pool of candidates that are ultimately hired? Blinding may improve the average quality of candidates selected through multiple channels. First, recruiters may hire higher-performing candidates on average when the possibility of age and gender discrimination is eliminated, relying exclusively on other signals of performance. Second, blinding may draw in a larger pool of talented candidates, particularly high quality counter-stereotypical candidates who may have chosen not to apply due to anticipated discrimination in a non-blind hiring process. Our setup allows us to investigate the distribution of performance and the age and gender diversity of the applicant pool and the hired pool under a variety of conditions, including both observed and counterfactual scenarios.

4 Results

We start by exploring candidate behavior, comparing application decisions across blind and non-blind hiring processes both before and after rejection. Then, we turn to recruiter decision-making and compare recruiters' decisions to candidates' beliefs about blind hiring processes. Next, we consider the net effects of blind hiring processes in our setting, incorporating both supply and demand-side factors. Lastly, we present qualitative evidence on candidates' perceived experiences with recruiter discrimination beyond our experiment.

4.1 Initial Willingness to Apply

Panel A of Figure 1 presents the average willingness to apply under both non-blind and blind hiring processes, using data only from candidates' first two application decisions (before they have received negative feedback). To ease interpretation, we present the effects in standard deviation units.[10]

[10] We standardize over the full distribution of all willingness to apply observations, pooling over all four price-lists faced by candidates, allowing us to compare not only across sub-groups but also across treatments and pre- versus post-rejection. Panels A and B of Appendix Table A3 presents pre-standardized summary statistics.

4.1.1 Gender and Age Differences in Willingness to Apply

Panel A of Figure 1 splits the data first by gender, comparing men and women, and then by age, comparing younger individuals to older individuals. We hypothesize that counter-stereotypical candidates will be less likely to apply. This could be driven by more pessimistic beliefs about own ability, i.e. self-stereotyping, and in the case of non-blind hiring, anticipated discrimination. Indeed, we observe that, on average, women and older individuals are less willing to apply (relative to men and younger individuals, respectively).

Column 1 of Table 1 presents results on willingness to apply before rejection, controlling for other resume characteristics. Looking first at non-blind decisions, we observe that women are significantly less willing to apply than men. On average, women require an outside option of 0.23 SDs less than men before they opt out of applying. We also see a significant (but smaller) gap in willingness to apply by age, of approximately 0.10 SDs. These gaps remain when we move to blind applications, with women (relative to men) and older individuals (relative to younger) being less willing to apply. However, the size of the gaps is somewhat reduced, as women and older individuals increase their willingness to apply with blind resumes. Blinding reduces the gender and age gaps by approximately 25% ($p < 0.01$ for the reduction in the gender gap, $p \approx 0.29$ for the reduction in the age gap). We estimate that moving to blind applications has no impact on the willingness to apply of young men.

We ask individuals a variety of questions regarding their application choices. Many of these measures point to self-stereotyping as a primary factor in women's lower application rates. Individuals provide an incentivized guess of their performance on the 10-question technical test. Conditional on their performance and other resume characteristics, women estimate a score 0.65 points worse than men ($p < 0.01$, see Appendix Table A4). Appendix Table A5 presents other proxies for confidence. We ask individuals what sample performance they believe will be displayed on their resume, 0, 1, or 2. Conditional on their technical test score and other resume characteristics, women estimate a sample performance 0.2 points worse than men ($p < 0.01$, column 1). Women also report feeling significantly less qualified than men, rating themselves more than 0.5 points less qualified on a 7-point scale compared to men with the same resume and test score ($p < 0.01$, column 4). Interestingly, we do not see a similar self-stereotyping gap in terms of age. Conditional on technical test score and other resume characteristics, older individuals actually anticipate a significantly better sample performance than younger individuals (by 0.09 points, $p < 0.01$); and, there is no age gap in believed total test score or believed qualification level (see Appendix Table A4 and A5). In our setting, self-stereotyping seems much more relevant for understanding gender differences than age differences.

We can add to our specification from Table 1 proxies for an individual's self-confidence (their believed score on the technical test) and risk preferences (their self-reported willingness to take risks on our survey measure). Appendix Table A6 shows the results, splitting our sample before rejection by application type. We observe that both self-confidence and risk preferences are significant predictors of application decisions, with more self-confident individuals and more risk-tolerant individuals applying significantly more often. This is true for both blind and non-blind applications. However, larger gender and age gaps remain after controlling for beliefs and risk preferences in the non-blind treatment, suggesting another important force at work - likely anticipated discrimination - when applications are not blind.

4.1.2 Initial Demand for Blinding

Column 1 of Table 3 zooms in on the relative demand for blind applications across different candidates. We predict the difference in willingness to apply under the blind relative to non-blind process, interpreting this difference as the revealed demand for blind applications. Women's demand for blinding is 0.07 SDs, significantly greater than 0 ($p < 0.01$), and their demand for blinding is significantly greater than men's (by approximately 0.06 SDs, $p < 0.01$). Turning to age, we cannot reject that the demand for blinding is the same across younger and older individuals (0.01 SDs compared to 0.04 SDs, $p \approx 0.22$).

Our data allows us to link this demand for blinding to anticipated discrimination. First, we ask individuals to assess their relative likelihood of being hired when submitting a blinded resume compared to a non-blind resume (on a 7-point scale ranging from much more likely to be hired under a non-blind process to much more likely to be hired under a blind process). Results are in Appendix Table A12. Women report a significantly greater anticipated benefit to blind applications compared to men, by nearly a full point ($p < 0.01$); older individuals also anticipate significantly greater benefits to blinding than younger individuals (by roughly 0.6 points, $p < 0.01$).[11] We can also use across-subject data to explore this issue. Individuals are randomly assigned to consider one of their resumes (either the blind or non-blind) and asked their believed likelihood of being hired with this resume. Results are presented in Panel C of Table A5. Among individuals asked to consider non-blind resumes, women and older individuals both perceive a significantly lower likelihood of being hired (by 7pp for women compared to men, $p < 0.01$, and by 3pp for older compared to younger, $p < 0.05$). There are no gender or age gaps in believed likelihood of being hired among individuals asked to consider their blind resumes.

Participants are also asked their beliefs about which resume characteristics would likely be responsible for them being rejected (and, separately, which resume characteristics would be responsible for them being hired). We calculate a candidate's expected "net" effect of a characteristic by differencing out the points assigned to the characteristic's role in rejection and the characteristic's role in being hired. Figure A1 shows that counter-stereotypical candidates are indeed more likely to anticipate net discrimination against them, with women anticipating more gender discrimination than men and older individuals anticipating more age discrimination than younger individuals. These beliefs map into their application decisions. Figure 3 shows that counter-stereotypical candidates who anticipate recruiter discrimination against their type reveal a significantly greater demand for blind applications. By contrast, those who expect favorable discrimination show little to no preference between blind and non-blind applications, indicating that anticipated discrimination plays an important role in driving the demand for blinding.

Our survey also asks about another potential driver of demand for blinding: anticipated disappointment or frustration. We asked individuals to imagine they were rejected on their selected resume. How disappointed or frustrated would they feel? One possibility is that a non-blind rejection, potentially due to discrimination, might be seen as particularly disappointing or frustrating. Indeed, our data seems consistent with this story. Overall, individuals asked to imagine a non-blind rejection anticipate significantly more disappointment than individuals asked to imagine a blind rejection ($p < 0.01$, Appendix Table A8). However, this does not vary by gender or age.[12]

[11] The mean Likert scores for the different groups are: 3.0 for women, 4.0 for men, 4.2 for younger candidates, and 4.8 for older candidates. In fact, the majority of women (68%, compared to 41% of men) and of older candidates (62%, compared to 48% of those under 45) responded that it was at least somewhat likely they had better chances of being hired with the blind resume.

[12] Mean expected disappointment is 5.0 for the non-blind resume, compared to 4.4 for the blind resume.

Both men and women and older and younger individuals anticipate greater disappointment after a non-blind rejection. This points to another reason why individuals may prefer blind application processes, as they anticipate that they will reduce psychological costs such as disappointment or frustration after rejection.[13]

We have shown that blinding grows the candidate pool. It does not decrease application rates among young men, while increasing application rates among women and older individuals. From an employer perspective, the supply-side benefits of a blind application process are larger if the switch attracts talented candidates in particular. To explore this, we can look at heterogeneity in the demand for blind applications by candidate ability as measured by score on the technical test. Figure 2 presents the results. Panel A of Figure 2a shows demand for blinding among applicants with test scores between 0 - 5, while Figure 2b shows demand for blinding among the most talented applicants, those with test scores greater than 5 (approximately the top 25% of the sample). We observe that demand for blinding is generally larger among more talented candidates, particularly talented women.[14] This highlights the potential of blinding to increase the supply of talented, counter-stereotypical candidates.

4.2 The Impact of Rejection on Applications

After they indicate their willingness to apply under both blind and non-blind processes, all candidates in our study receive negative feedback on one of their applications. Either the blind or non-blind application is randomly selected for a candidate. Then, the candidate is informed that one recruiter chose not to hire someone with that resume. This allows us to consider the impact of rejection on the full sample of candidates, independent of candidate ability or application decisions.

In line with expectations, we find a negative impact of rejection on willingness to apply again (see Figure 1). Overall, we observe that individuals are approximately 0.25 SDs less willing to apply post-rejection ($p < 0.01$, Column 1, Table 2). We can also look at our companion measures to get a better sense of what contributes to this deterrence effect. Primarily, we see evidence of candidates updating their beliefs about their abilities following a rejection. Appendix Table A5 presents the

[13]We do not observe age or gender differences in anticipated disappointment overall, regardless of whether the rejection would be blind or non-blind. This suggests that differences in these types of anticipated psychological costs do not seem to be a factor in explaining gender or age gaps in willingness to apply.

[14]We observe similar results if we do a median-split on candidate test score.

results, with the coefficient on post-rejection in Column 1 providing the relevant estimates. When asked what they believe the sample performance shown on their resume was, candidates believe they likely had a sample performance 0.4 points worse after rejection compared to before ($p < 0.01$). Candidates also feel significantly less qualified after rejection compared to before (by 0.10 points on a 7-point scale, $p < 0.01$). When asked about their believed likelihood of being hired were they to apply again to a similar opportunity, individuals believed likelihood of being hired is 6.5pp lower after rejection ($p < 0.01$).

4.2.1 Comparing Responses to Blind and Non-Blind Rejections

We can return to Figure 1 to explore how reductions in willingness to apply depend upon the type of rejection. Panel B plots willingness to apply after a non-blind rejection, while Panel C plots willingness to apply after a blind rejection. We observe that blind rejections have a significantly larger deterrence effect than non-blind rejections. In a regression model that controls for technical test score and resume characteristics, we estimate that a blind rejection reduces willingness to apply by nearly 40% more than a non-blind rejection (Column 1, Table 2, $p < 0.01$).

Why does a blind rejection deter future applications more? Candidates may interpret blind rejections as stronger signals of their qualifications and skills. While rejection on a non-blind resume could potentially be explained via discrimination, rejection on a blind resume leaves less room for this interpretation. Our additional measures in Table A5 provide some support of this view. Consistent with stronger updating on skills, individuals revise down their beliefs of how qualified they are by more after a blind rejection compared to a non-blind rejection (Column 5 versus Column 6). Similarly, for women and younger candidates, a blind rejection reduces the believed likelihood of being hired by more than a non-blind rejection (Column 8 and Column 9). However, candidates do not adjust their believed sample performance more after a blind rejection compared to a non-blind rejection (Column 2 versus Column 3).

It does not appear to be the case that blind rejections cause greater deterrence because of their associated psychological costs. Recall that prior to rejection, individuals anticipate that a blind rejection would be significantly less disappointing than a non-blind rejection. After rejection, this view persists. Table A8 shows the results on feelings of disappointment, with Column 1 presenting results on anticipated feelings prior to rejection and Column 2 presenting results on experienced feelings after rejection. Individuals who were rejected blind express significantly less disappointment with their rejection compared to individuals who were rejected non-blind (0.6 points, Column 2, $p < 0.01$). We also ask participants how fair they believe their rejection was. Individuals rejected based on a blind resume rate their rejection as somewhat more fair than individuals rejected based on a non-blind resume (by 0.2 points, Column 3, $p < 0.10$). Thus, while blind rejections seem to have a more negative impact on candidates' beliefs of their own skills and their willingness to apply again in the future, they do not seem to have greater psychological costs, consistent with findings in the literature on procedural fairness (Brockner and Wiesenfeld, 1996).

4.2.2 Comparing Responses to Rejection by Gender and Age

Overall, the deterrence effect of rejection does not vary strongly with gender or age. Average willingness to apply falls by a similar amount for both women and men as well as older and younger individuals (Table A11, Column 1). As a result, the gender and age gaps in overall willingness to apply do not increase post-rejection in our setting.[15]

But, these overall drops in willingness to apply mask important heterogeneity in reactions to blind versus non-blind rejections across age and gender (see Figure 1). The relatively larger impact of blind rejections on willingness to apply is driven by counter-stereotypical candidates. As Table 2 shows, women's willingness to apply drops by twice as much after a blind rejection than after a non-blind rejection ($p < 0.01$, column 3), and older individuals' willingness to apply drops by 50% more after a blind rejection than after a non-blind rejection ($p < 0.01$, column 5). For young men, there is no significant difference in deterrence after a blind versus non-blind rejection.

This heterogeneity in deterrence effects has important implications gender gaps under blind versus non-blind processes. After a non-blind rejection (Table A11, Column 2), women are approximately 0.14 SDs less willing to apply than men ($p < 0.10$). This gap is significantly smaller than the gender gap observed before the non-blind rejection ($p < 0.05$), with men adjusting their willingness to apply down more following the non-blind rejection. A blind rejection, on the other

[15]The supplementary measures tell a similar story, see Table A5, Column 1. Women do not update their beliefs of their sample performance or their qualification level more negatively than men. However, they do experience a bigger reduction in their believed likelihood of being hired post-rejection (9pp compared to 7pp, $p < 0.05$, Column 7). Older individuals experience a relatively larger drop in how well-qualified they feel post-rejection compared to younger individuals ($p < 0.05$, Column 4), but they do not update their believed sample performance or believed likelihood of being hired anymore than younger individuals do.

hand, widens the gender gap in overall willingness to apply (Table A11, Column 3), from an estimated to 0.22 SDs to 0.33 SDs ($p < 0.01$ testing for a gender gap after blind rejection, $p < 0.05$ for the difference-in-difference before and after rejection).[16] Rejection has no significant impact on the age gap, regardless of whether it was blind or non-blind (see Columns 2, 3 of A11).

When we look at believed likelihood of being hired, we observe a similar pattern. Candidates see themselves as less likely to be hired in the non-blind treatment post-rejection (by approximately 7pp, $p < 0.01$, Appendix Table A5, Column 8), but this is no more true for women or older individuals than others. When the rejection was a blind rejection (see Appendix Table A5, Column 9), however, it has a particularly large impact on the believed likelihood of being hired among women and older individuals. Young men's believed likelihood of being hired falls by 6pp ($p < 0.01$), while women's falls by 11pp ($p < 0.01$ on the difference-in-difference) and older individuals' falls by 9pp ($p < 0.05$ on the difference-in-difference).

These results paint a more nuanced story of the impact of blind hiring processes. Initially, blind hiring processes serve to reduce gender gaps in willingness to apply relative to non-blind processes. But, rejection under these blind processes has a larger impact. Blind rejections widen gender gaps in willingness to apply relative to non-blind rejections (see Appendix Table A9). Pooling across post-rejection application types, we estimate that the gender gap in willingness to apply is twice as large after a blind rejection than after a non-blind rejection, estimated at roughly one-third of a standard deviation (column 1, $p < 0.05$). Similarly, we estimate a significantly larger age gap in willingness to apply after blind rejection than non-blind rejection (Column 1, $p < 0.10$).

4.2.3 Impact of Rejection on Relative Demand for Blinding

The previous sections considered responses to rejection on willingness to apply going forward, pooling across different future application types. In this section, we consider the impact of rejection on demand for blinding; that is, how does rejection change preferences for blind relative to non-blind applications moving forward? Does this depend upon whether the rejection was blind or non-blind?

Table 3 compares demand for blinding (willingness to apply on blind relative to non-blind

[16] Note that these results pool application types, looking at average willingness to apply across both types of hiring processes, before and after a blind versus non-blind rejection. In Section 4.2.3, we unpack differential impacts of rejection on blind versus non-blind applications.

applications) pre-rejection and following rejection on either a non-blind or blind resume. Column 1 shows that, overall, rejection does not significantly change demand for blinding. However, women and older candidates increase their demand for blinding somewhat more than men and younger candidates after rejection ($p < 0.10$ for both effects).

Column 2 of Table 3 reveals that, following a non-blind rejection, demand for blinding is significantly greater among women than men (by 0.12 SDs, $p < 0.05$) and older individuals compared to younger individuals (by 0.10 SDs, $p < 0.10$). These patterns are consistent with the idea that following a non-blind rejection, candidates adjust their beliefs about recruiter discrimination against their type. Figure 3b shows that both men and women, and both younger and older candidates, who believe gender (age) was a reason for rejection increase their relative demand for blinding after a non-blind rejection. This highlights how rejection, through its impact on perceived discrimination, can influence candidates' future application decisions and preferences for blind processes.

A blind rejection, on the other hand, marginally decreases demand for blind application processes as shown in Column 3 of Table 3. Relative demand for blinding is similar pre- and post-blind rejection among women and older individuals, while we observe that relative demand for blinding falls among young men, who would likely benefit from age and gender stereotypes ($p < 0.10$). In fact, post-rejection on a blind resume, men are significantly more willing to apply on non-blind applications than blind applications going forward, perhaps anticipating that gender discrimination could benefit them (Column 4 of Table 1).

4.3 Discrimination in Hiring: Recruiter Behavior and Candidate Beliefs

We now turn to our recruiter data to document the extent of age and gender discrimination in willingness to hire. We then compare recruiters' discriminatory behaviors with candidates' beliefs about the extent of discrimination. Recall that recruiters were randomly assigned to evaluate either five blinded resumes or five non-blinded resumes. We observe that blinding resumes does not significantly shift willingness to hire on average (see Appendix Table A13). Our focus is whether blinding resumes increases the likelihood of hiring counter-stereotypical candidates and/or decreases the likelihood of hiring men and younger workers. As with candidates, we present recruiter willingness to hire effects in standard deviation units.[17]

Our recruiters can base their decisions on a candidate's educational background, favorite subject, sample performance, and, in the case of the non-blind treatment, their age and gender. Table 4 illustrates the estimated impact of each resume characteristic on the likelihood of a candidate being hired, breaking the data out by treatment. Candidates' performance on the test is the factor that weighs the heaviest in recruiters' willingness to hire, with a large premium for a sample performance of 2/2 on the test. This is true in both the non-blind resume evaluations (Column 1) and in the blind evaluations (Column 5). In both treatments, recruiters also place significant value on education, paying a premium for workers with a bachelors or advanced degree. They are also significantly more willing to hire workers who list STEM as their favorite subject.

We can measure recruiter discrimination in the non-blind treatment. We find that, conditional on other resume characteristics, recruiters are significantly less likely to hire women (Column 1 of Table 4, $p < 0.05$). While the overall effect is modest, estimated at 0.06 SDs, discrimination is more pronounced for women with better performance signals; Column 4 presents the results for individuals with a sample performance of 2/2 on their resume. In this case, we estimate that women are 0.20 SDs less likely to be hired than men with identical resumes ($p < 0.01$). We do not observe statistically significant discrimination against older workers. Conditional on other resume characteristics, we estimate that recruiters are approximately 0.05 SDs less likely to hire older candidates compared to younger candidates (Column 1 of Table 4, $p \approx 0.13$.). This effect appears to be similar across different performance signals (see Columns 2, 3, and 4). In sum, recruiters appear to discriminate most against more skilled women, with little to no discrimination estimated against other types. Appendix Figure A2 shows the rate at which recruiters hire men, women, younger and older workers, breaking out the sample according to candidate quality. We see that, consistent with Table 4, counter-stereotypical candidates with stronger signals of performance face more discrimination.

While our study is not designed to unpack the sources of recruiter discrimination, we do have some evidence on recruiter beliefs. We ask all recruiters to estimate the average test score for candidates of different types (see Appendix Table A14). Both male and female recruiters have

[17]We standardize over the full distribution of all willingness to hire observations, pooling over all five price-lists faced by recruiters, allowing us to compare not only across sub-groups but also across treatments. Panel C of Appendix Table A3 presents pre-standardized summary statistics.

roughly accurate beliefs about the size of the gender gap in performance (roughly 0.40 points). However, recruiters substantially overestimate the age gap in performance. While the true gap is roughly 0.30 points, recruiters believe the gap is closer to 1 point on average. Our results perhaps help to illustrate that beliefs about average performance differences may be less informative about patterns of discrimination, even belief-based discrimination, in situations where recruiters have access to multiple signals of performance.

Our data can speak to how observed discrimination compares to anticipated discrimination. We asked candidates whether they believed men (women) would be more likely to be hired by recruiters when resumes were non-blind compared to blind, with candidates answering on a 1-5 point Likert scale. Overall, candidates believe men benefit significantly more from a non-blind resume compared to women (3.6 for men v. 2.6 for women, $p < 0.01$). This difference is even more pronounced among women, who anticipate an even larger gender gap in the extent to which candidates benefit from a non-blind resume (Appendix Table A16, Columns 1 and 2). Similarly, overall individuals believe that younger candidates are significantly more likely to benefit from non-blind resumes than older candidates (3.6 v. 2.2, $p < 0.01$). And, older individuals anticipate a significantly larger age gap in the benefits of a non-blind resume compared to younger individuals (Appendix Table A16, Columns 3 and 4).

We asked candidates their beliefs on which of their resume characteristics would be relatively more beneficial for their application, prior to receiving any feedback. They had to assign weights to each of their resume characteristics, with the weights summing to 100, first in the hypothetical case that they were hired (i.e. if you were hired how much do you think each of these characteristics contributed to that outcome) and then in the hypothetical case that they were not hired (i.e. if you were not hired, how much do you think each of these characteristics contributed to that rejection). Panel A of Figure A1 presents a histogram of anticipated net gender discrimination for men and women in the non-blind treatment (the difference in how much a candidate believed gender would contribute to them being rejected versus hired). Women are more likely than men to anticipate gender discrimination, with nearly half of women anticipating some degree of discrimination against them based upon their gender. Men are more likely to believe their gender will help their application chances rather than hurt them. Panel B displays the results for anticipated net age discrimination for younger and older candidates. Older candidates are very likely to anticipate discrimination based upon their age, with close two-thirds of older candidates anticipating net discrimination based upon their age. Younger candidates are equally likely to believe their age will have no impact, positive impact, or negative impact on their application chances.

Note that these perceptions align with their stated perceptions about discrimination in the broader labor market. More than half of women indicate that they are at least somewhat worried about gender discrimination in the labor market, compared to just over 20% of men. We observe interesting patterns in age, with close to 80% of older individuals in our study indicating that they are at least somewhat worried about age discrimination in the labor market and also more than 50% of younger individuals also indicating some degree of worry.[18] On a 7-point scale, we estimate that women are 1.2 points more worried than men about gender discrimination (A17, Column 1, $p < 0.01$) and older individuals are 1.4 points more worried about age discrimination than younger individuals (A17, Column 2, $p < 0.01$). On the whole, anticipated discrimination seems to be a significant concern among our sample, both in the context of our experiment and more broadly. Within our study, candidates who say that they are worried about being discriminated against by recruiters because of their gender or age have greater demand for blind application processes on average (see Figure 3).

Together, this more qualitative evidence points to anticipation of rather large degrees of gender and age discrimination against counter-stereotypical candidates. To compare these perceptions more directly with observed discrimination, we can use candidates' quantitative beliefs. Figure 4 shows the return to blinding an application in terms of hiring probability, with Panel A documenting the observed benefits based upon recruiter decisions, Panel B documenting candidate pre-rejection beliefs in terms of perceived likelihood of being hired, and Panel C documenting candidate post-rejection beliefs in terms of perceived likelihood of being hired. Starting with Panel A, we estimate no return to blinding for men or for younger candidates in our sample and a modest benefit to blinding for women and older individuals in our sample (approximately 2pp). Turning to Panel B, we see that counter-stereotypical candidates overestimate the returns to blinding pre-rejection,

[18] At the end of the survey, candidates could add open-ended comments. Many respondents wrote about their experiences with age discrimination. For instance, one writes: "Ageism is a real thing. I have been rejected for my age and its funny, I am an energetic 57 and will have to work another 20 years in this economy. I have more common sense, life experience and organization that anyone in their 20s." Another writes: "I work remotely. I and most of my work chat colleagues have several resumes, in particular ones where we can hide our age. A lot of us try to avoid video interviews too."

with women believing they will be approximately 5pp more likely to be hired with a blind resume and older individuals believing they will be approximately 4pp more likely to be hired with a blind resume. Interestingly, rejection eliminates the perceived benefits of blinding for all candidate subgroups (Panel C), with women and older individuals no longer believing they are significantly more likely to be hired with a blind application than a non-blind application.

In sum, our evidence points to counter-stereotypical candidates anticipating significant degrees of discrimination under non-blind application processes, whether measured with qualitative or quantitative data and whether focused on our study or more broadly. Yet, anticipated discrimination seems to exceed observed discrimination in our study, as we observe modest recruiter discrimination, largely concentrated against more talented women. Consistent with this pattern, candidates also seem to over-estimate the benefits of blinding. Both candidate beliefs and willingness to apply indicate that counter-stereotypical candidates anticipate a significant return to blind applications, at least prior to receiving negative feedback, while recruiter behavior suggests more limited benefits to blinding for counter-stereotypical candidates than anticipated by candidates themselves.

4.4 Net Effects of Blinding

Our results illustrate two channels through which blind hiring processes may change the pool of hired candidates: (i) eliminating recruiter discrimination (in our case against talented women) and (ii) increasing the rate at which counter-stereotypical candidates apply. In this section, we explore the net effects of these channels.

We consider the impact of blinding on two outcome variables. The first is the average productivity of hired candidates, as measured by their technical test scores (the payoff-relevant outcome for recruiters). The second is the share of women and older candidates among the set of hired candidates. Of course, the impact of blinding may depend on the tightness of the market. We use our data to simulate different labor market conditions, including a tight market (in which only the top 10% of candidates are hired), a slack market (in which the top 80% of candidates are hired), and a market in between (in which the top 40% of candidates are hired).[19]

[19] We choose these cutoffs as they correspond to different technical test thresholds. For instance, the top 10% of workers corresponds to workers with technical test scores greater than or equal to 7, the top 40% corresponds to technical test scores greater than or equal to 5, and the top 80% corresponds to technical test scores greater than or equal to 3. Choosing cutoffs that correspond to technical test scores allows for straightforward computation of the maximum achievable average productivity for recruiters at these different levels of market tightness.

We use our data to simulate the pool of hired candidates under blind and non-blind hiring processes for different levels of market tightness.[20] For reference, we also present two counterfactuals: (i) the outcomes if recruiters were able to perfectly observe productivity (test scores) and simply hired the candidates with the top X% of test scores and (ii) the outcomes if candidates were hired at random.

Table 5 presents the results. Note that across all levels of labor market tightness, recruiters are selecting candidates with higher rates of productivity then would be achieved at random while falling well short of maximum achievable productivity. When we consider a tight labor market, we see that the blind hiring process dominates the non-blind hiring process in terms of our outcomes of interest. The blind hiring process delivers candidates with higher average productivity and increases the share of women and older candidates hired. As the labor market grows slacker, this pattern weakly holds, though the gains in productivity and representation shrink. In the most slack market we estimate, outcomes under blind and non-blind hiring processes are nearly identical. This may relate to the fact blinding seems to have the largest impact on the most talented candidates (both in terms of willingness to apply and in terms of reduced discrimination), who are highly likely to be hired under either process in a slack market.

4.5 Survey Evidence on Perceptions of Blind Hiring Processes

We complemented our experimental approach to investigating the impact of blind hiring processes on the supply of candidates with more direct survey questions on individuals' perceptions and preferences. In this section, we detail that survey evidence, contributing to our understanding of how candidates view blind hiring processes.

We asked candidates whether they prefer their demographic information be included in their application when they are applying to jobs (1-7 point scale, from strongly prefer to include to strongly prefer to exclude). More than half of our sample expresses a strict preference for excluding their demographics, but we observe significant heterogeneity. Fewer than 40% of young men prefer

[20] To select the pool of hired candidates under a blind (non-blind) process, we assume candidates apply at their blind (non-blind) pre-rejection rates. We first determine the probability with which a candidate applied (average application rate over non-dominated rows of the price list). Then, we determine the likelihood of this candidate being hired given blind (non-blind) recruiter decisions (average share of recruiter decisions in which they chose to hire a candidate with that resume across non-dominated price-list rows, multiplied by the candidate's likelihood of applying). The hired pool of candidates is then the X% of candidates with the highest likelihood of being hired according to this metric, where X corresponds to the tightness of the market.

blind hiring processes. On our 7-pt scale, we observe a greater preference for blind hiring processes among women (by 0.6 points, $p < 0.01$, Column 1 of Table 6) and older individuals (by 0.3 points, $p < 0.01$).

We also wanted to understand what might lead individuals to prefer blind or non-blind hiring processes. In a first series of questions, we gave candidates five different statements about non-blind hiring processes and asked them to indicate on a 1-5 scale their level of agreement with the statement (see Appendix Table A18). First, we asked whether including their demographic characteristics would help them to get an interview. Average agreement was approximately 2.5, with women and older individuals significantly less likely to agree. Then, we asked whether including their demographic characteristics supported diversity, equity, and inclusion in the workplace. Average agreement was approximately 3.1, with women and older individuals significantly more likely to agree. We asked whether they agreed that including their demographics allowed them to filter out discriminating employers, with individuals indicating an average agreement of 3.2. Again, women are significantly more likely to agree with this statement (no significant age differences, Column 3). We see similar patterns of agreement with the statement that revealing their demographics would allow them to show a part of their identity that they were proud of (approximately 3.1 on average, significantly greater agreement among women, Column 4). Finally, we wanted to understand whether being hired under a process that included demographic characteristics would create doubt in individuals as to whether they were hired based upon competence or identity (Column 5). Women are significantly more likely to agree with this statement, with average agreement around 3.0. Together, these responses illustrate moderate endorsement of many possible benefits of non-blind hiring processes, with important heterogeneity across candidates. Table 6 shows that these perceptions correlate with demand for non-blind application processes, with interview considerations having the largest predictive power. For instance, 69% of candidates who agree that revealing their demographics will help them get an interview prefer non-blind applications over blind applications.

We also ask candidates to reflect on how they would feel if offered (or not offered) an interview under different hiring processes. We present the results in the first two columns of Appendix Table A19. Candidates are asked to imagine they received an interview request and to report whether they would feel better about that request if their demographic characteristics had been included on their application (Column 1). They respond on a 5-point scale where 1 indicates that they would feel much better if their demographics had been included on the application and 5 indicates that they would feel much better if their demographics had been excluded. The average response is 2.8, suggesting that on average people would have felt better had they received the interview request in a non-blind process. We see no significant gender differences, but older individuals indicate a significantly weaker preference for having received the interview through a blind process. Conversely, we also ask candidate to imagine being denied an interview and to report whether they would feel better about this rejection if their demographic characteristics had been included on their application (Column 2). On average, people seem to feel better about a rejection if it resulted from a blind process (average response of 3.5), consistent with candidates feelings about disappointment and fairness within our experimental context. This is driven, in part, by significantly stronger agreement with this sentiment among women.

The remaining columns of Appendix Table A19 speak to the perceived benefits of blind hiring processes. Again, candidates are asked to indicate their agreement with a list of statements related to blind hiring processes, this time on a 1-7 scale.[21] On average, candidates agree that blind processes lead to more diverse applicant pools (4.8, Column 3), lead to more diverse workforces (4.72, Column 4), lead to more productive workforces (4.68, Column 5), and that they should be standard practice for all employers (4.88, Column 6). The only significant difference by individual demographics is that women are significantly more likely to agree with the statement that blind hiring processes should be standard practice (by 0.2 points, $p < 0.01$, Column 6).

Taken together, our evidence points to significant support for blind hiring processes from the candidate perspective, with notable heterogeneity by candidate demographics. Women express significantly greater support for blind hiring processes. Looking at potential explanations, this seems to be in part because (i) they perceive lower benefit to including their demographics on applications (in terms of likelihood of receiving an interview) and (ii) they express greater doubt about the reasons underlying an interview request that results from a non-blind process. It is important to emphasize that the results for women do not generalize to other stereotyped groups, with significant variation in the patterns of agreement with different arguments related to blind hiring

[21]Switching from a 5-point to a 7-point agreement scale was an unintentional error. As a result, we use caution in comparing responses to statements about non-blind compared to blind hiring processes. However, comparisons within process type should be unaffected.

processes. Age differences in support for blind hiring process are smaller than gender differences. This suggests the need for more work investigating candidate perceptions and behavior under both blind and non-blind hiring processes.

5 Conclusion

We explore the impact of blind hiring processes on labor market outcomes, with a particular focus on how blind hiring processes impact the supply of candidates. Our results reveal that counter-stereotypical candidates, in our case women and older workers, are significantly more willing to apply when the hiring process is blind. These results are, in part, driven by anticipated discrimination. Most counter-stereotypical candidates expect discrimination under non-blind hiring processes, and this may suppress the rates at which they apply. Importantly, we observe that these effects are stronger among more talented candidates, particularly talented women.

We use our data to simulate the net effects of blinding under different labor market conditions. We find that across different levels of labor market tightness, a blind hiring process leads to weakly greater average productivity among hired candidates and weakly greater representation of women and older candidates. These gains result from two forces: the elimination of discrimination and an increase in candidate supply. Both of these forces seem to have the largest impacts on talented women.

Our results add to the growing body of work that illustrates the interconnected nature of candidate and recruiter decision-making. We highlight that changes on the demand-side of the market, in our case eliminating the possibility of discrimination, can have meaningful impacts on the supply-side of the market. This is consistent with evidence on other demand-side policy interventions such as gender quotas. Lab and field studies find that quota policies increase the supply of qualified women who apply and are most effective in increasing women's representation in contexts where they are underrepresented (e.g. Niederle et al., 2013; De Sousa and Niederle, 2022; Czibor and Dominguez Martinez, 2019). Similarly, Coffman et al. (2023) finds that reducing ambiguity in job ads, another demand-side intervention, also increases the supply of female candidates who apply.

A key contribution of our work is our analysis of reactions to rejection. We vary whether candidates experience a rejection under a blind hiring process or a non-blind hiring process, and we ask how these rejections impact future application decisions and their relative demand for blind hiring processes going forward. We find that rejections under blind hiring processes are perceived as significantly more fair. However, they have a significantly larger deterrence effect on future applications. This is consistent with the idea that while non-blind rejections may be rationalized via discrimination, blind rejections may be perceived as stronger negative signals of quality, impacting future application decisions even under blind processes. We also observe that relative demand for blinding is somewhat reduced after a blind rejection, an effect that is concentrated among candidates that would likely benefit from recruiter stereotypes (in our case, young men).

In our setting, the greater deterrence effects of blind rejections are concentrated among women. We estimate that blind rejections reduce women's labor market supply by nearly twice as much as non-blind rejections. Our work suggests the need for further study on the medium to long-run impacts of blind hiring processes on both supply and demand sides of the market. While blind hiring processes may increase candidate supply in the near-term, it is important to better understand how candidate decisions evolve as they receive feedback in the labor market. These "net" effects may vary depending on the tightness of the market (indicative of the rate at which candidates will receive negative feedback) and candidates' information about their own quality. Blinding could have important longer-run impacts on the demand-side of the market as well. As previous papers have suggested, to the extent that blind processes increase the rate at which talented counter-stereotypical candidates are hired, this could serve to reduce stereotypical beliefs among recruiters over time.

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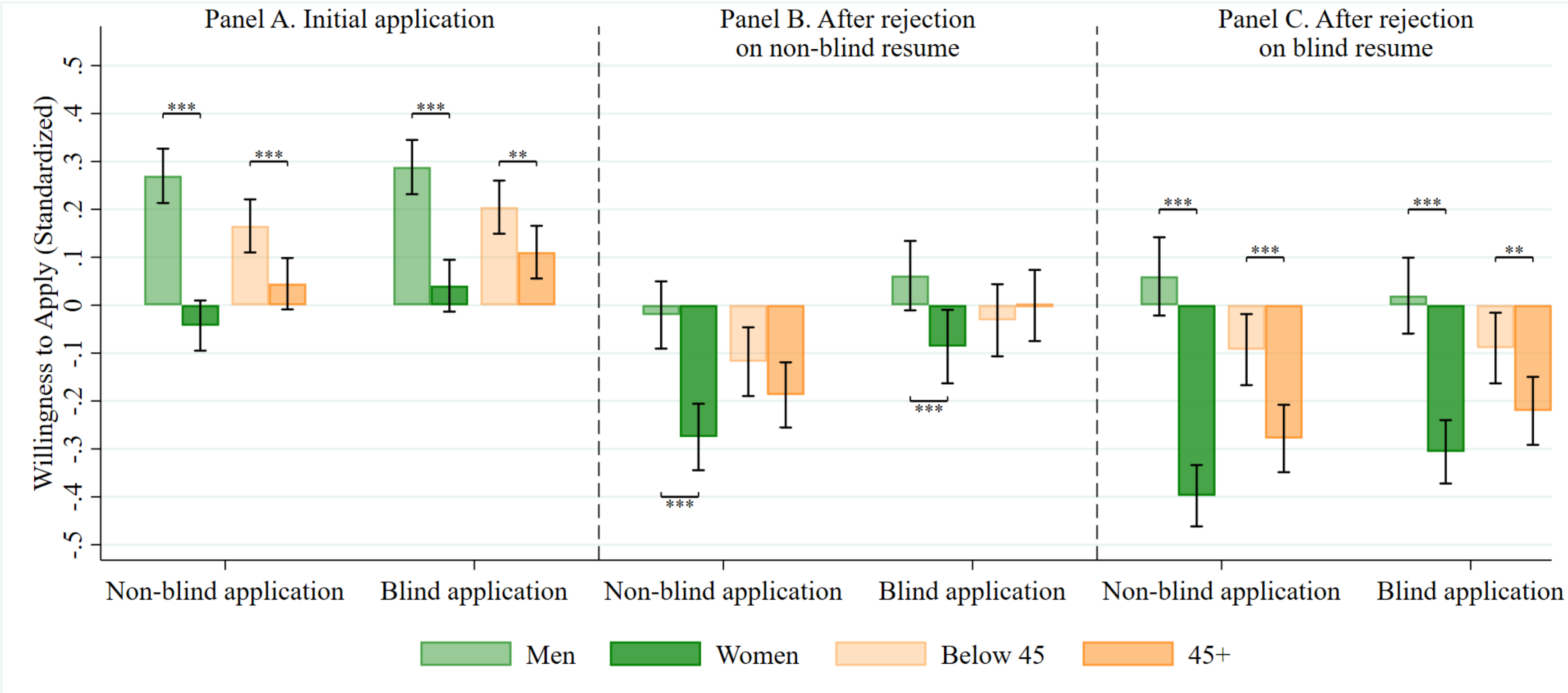
Figures

Figure 1. Average Willingness to Apply, by Gender and Age

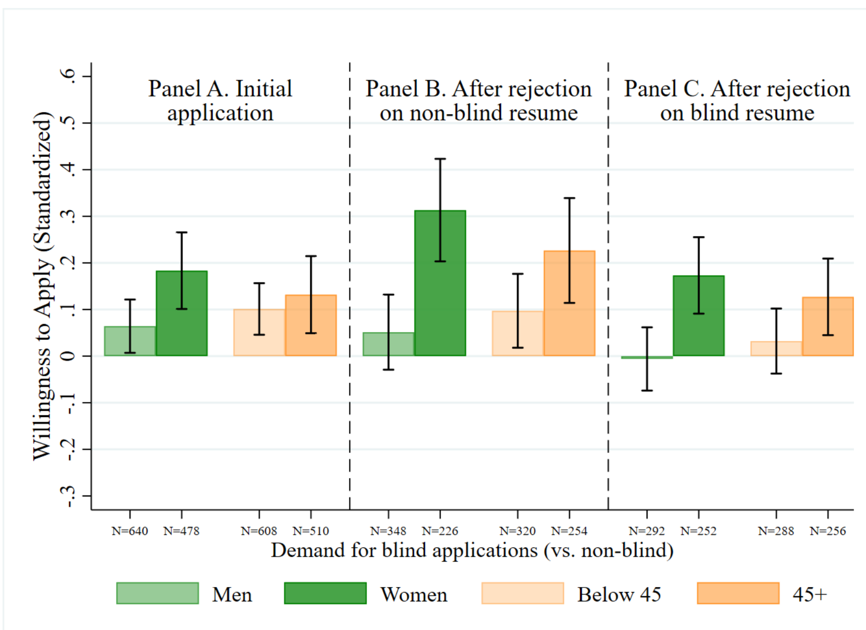


*Notes: Averages are calculated on standardized values. We standardize over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. Panel A includes all applications before rejection feedback ($N = 4,976$). Panel B includes application decisions after rejection for candidates who received feedback on their non-blind resume ($N = 2,472$). Panel C includes application decisions after rejection for candidates who received feedback on their blind resume ($N = 2,504$). Whiskers mark 95% confidence intervals. T-test significance levels: *** p<0.01 and ** p<0.05.*

Figure 2. Stronger Candidates Have Greater Demand for Blind Processes

(a) Test score between 0 and 5

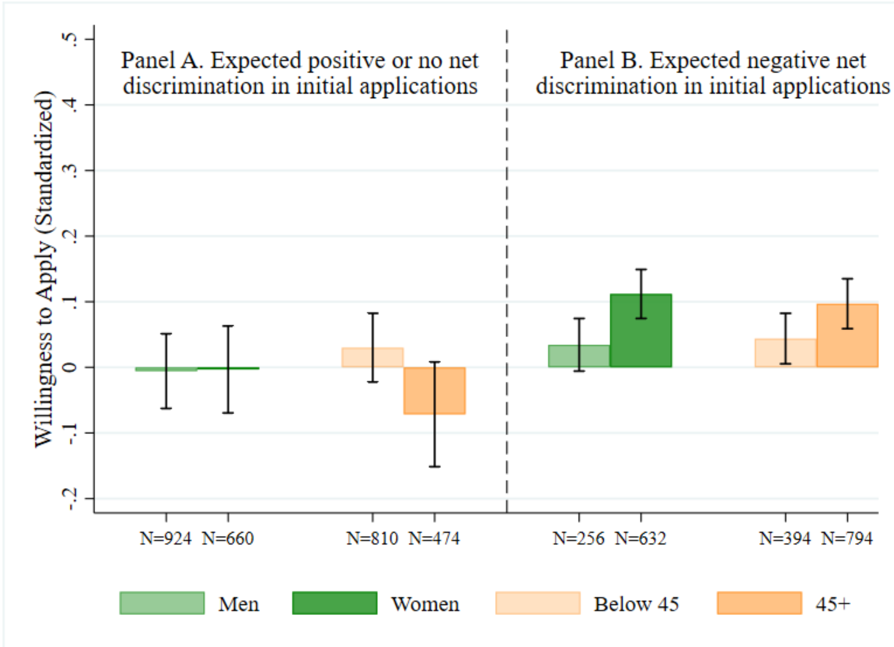
(b) Test score between 6 and 10



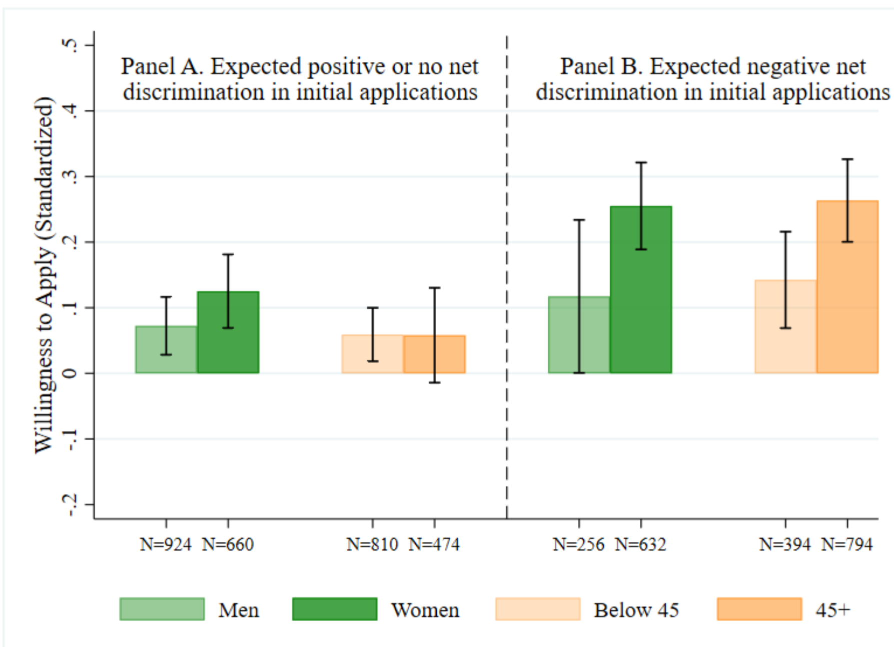
Notes: The figure graphs the average demand for blind applications. Demand for blind application is the difference in standardized willingness to apply under a blind process and standardized willingness to apply under a non-blind process, with positive values indicating greater demand for blind applications. Willingness to apply values are standardized over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. The top figure includes observations from candidates with a technical test score of 5 or less. The bottom figure includes observations from candidates with a technical test score of 6 or more. Whiskers mark 95% confidence intervals.

Figure 3. Anticipated Discrimination Predicts Demand for Blind Applications

(a) Initial applications

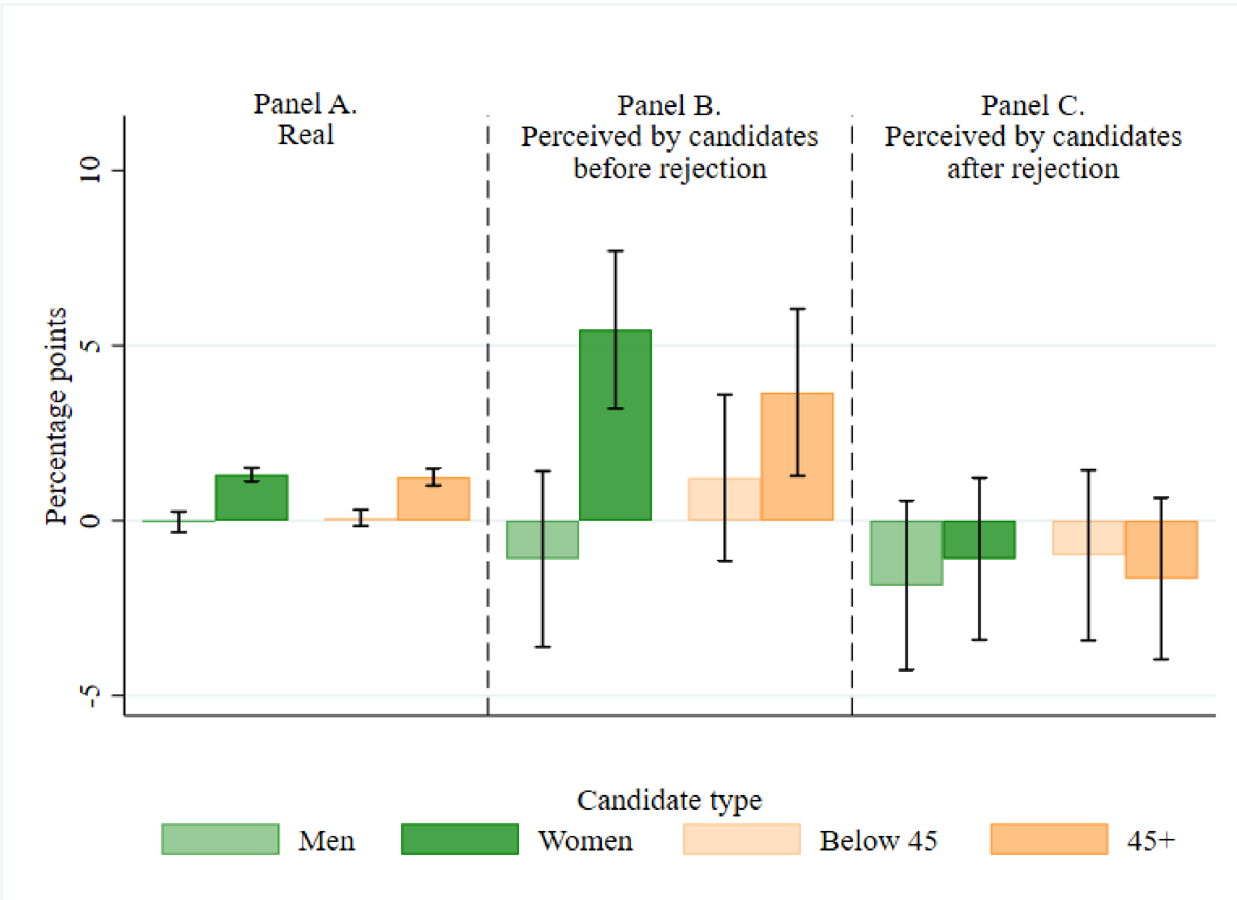


(b) After rejection



Notes: The figure graphs the average demand for blind applications before rejection (a) and after rejection (b). Demand for blind application is the difference in standardized willingness to apply under a blind process and standardized willingness to apply under a non-blind process, with positive values indicating greater demand for blind applications. Willingness to apply values are standardized over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. Panel A includes candidates who anticipate that, on net, their gender (age) would be more responsible for them being hired than being rejected. Panel B includes candidates who anticipate that, on net, their gender (age) would be more responsible for them being rejected than hired. Whiskers mark 95% confidence intervals.

Figure 4. Real and Perceived Benefit of Blinding in Terms of Hiring Probability



Notes: Panel A plots the estimated difference in likelihood of a candidate of that type being hired with a blind resume and a non-blind resume, with positive values indicating a greater likelihood of being hired based on a blind resume. Effects are estimated using an OLS regression that predicts a candidate's average likelihood of being hired by a recruiter from an indicator for whether their resume was blind or non-blind, estimated separately for men, women, younger, and older individuals. Standard errors are clustered at the candidate level. Panel B plots the average difference in believed likelihood of being hired based on a blind resume and a non-blind resume, using pre-rejection beliefs. Effects are estimated across-subject using an OLS regression that predicts a candidate's believed likelihood of being hired from an indicator for whether they were assigned to the blind or non-blind treatment, estimated separately for men, women, younger, and older individuals with controls for technical test score, favorite subject, education, age (for regressions by gender) and gender (for regressions by age). Panel C replicates Panel B but using post-rejection beliefs. Whiskers illustrate 95% confidence intervals.

Tables

Table 1. Willingness to Apply Before and After Rejection

Dependent variable:	Willingness to apply (standardized)			
		After rejection		
	Initial application	Pooled	Non-blind rejection	Blind rejection
	(1)	(2)	(3)	(4)
Blind application	0.01	-0.01	0.03	-0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
Women	-0.23***	-0.30***	-0.20***	-0.41***
	(0.04)	(0.04)	(0.05)	(0.05)
Age 45+	-0.10**	-0.12***	-0.07	-0.17***
	(0.04)	(0.04)	(0.05)	(0.05)
Blind application × Women	0.06***	0.11***	0.10***	0.13***
	(0.02)	(0.02)	(0.03)	(0.03)
Blind application × Age 45+	0.03	0.07***	0.10***	0.05*
	(0.02)	(0.02)	(0.03)	(0.03)
Controls				
Test score	X	X	X	X
Favorite subject	X	X	X	X
Education	X	X	X	X
Observations	4,976	4,976	2,472	2,504
R^2	0.08	0.08	0.08	0.10

*Notes: This table shows coefficient estimates from OLS regressions, where the dependent variable is standardized candidate willingness to apply. We standardize over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. All regressions include fixed effects for test scores, favorite subject, and level of education. Clustered standard errors at the candidate level are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table 2. Willingness to Apply Before and After Rejection, by Gender and Age

Dependent variable:	Willingness to apply (standardized)				
		By gender		By age	
	All	Men	Women	Below 45	45+
	(1)	(2)	(3)	(4)	(5)
Blind rejection	0.00	-0.00	0.00	0.05	-0.04
	(0.04)	(0.06)	(0.05)	(0.05)	(0.05)
Post-rejection	-0.22***	-0.26***	-0.18***	-0.24***	-0.20***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Blind rejection × Post-rejection	-0.08***	0.01	-0.17***	-0.06*	-0.10***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Controls					
Gender	X			X	X
Age	X	X	X		
Test score	X	X	X	X	X
Favorite subject	X	X	X	X	X
Education	X	X	X	X	X
Observations	9,952	4,636	5,316	4,800	5,152
R^2	0.09	0.09	0.07	0.09	0.10

*Notes: This table shows coefficient estimates from OLS regressions, where the dependent variable is standardized candidate willingness to apply. We standardize over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. All regressions include fixed effects for test scores, favorite subject, and level of education. Clustered standard errors at the candidate level are in parentheses. Significance levels: *** p<0.01 and * p<0.1.*

Table 3. Demand for Blind Applications, By Rejection Type

Dependent variable:	Difference in (standardized) Willingness to apply Blind − Non-blind		
	All (1)	Non-blind rejection (2)	Blind rejection (3)
Women	0.07***	0.07*	0.08**
	(0.02)	(0.04)	(0.03)
Age 45+	0.03	0.01	0.05
	(0.02)	(0.04)	(0.03)
Post-rejection	-0.02	0.02	-0.06*
	(0.02)	(0.04)	(0.03)
Post-rejection × Women	0.05*	0.05	0.06
	(0.03)	(0.04)	(0.04)
Post-rejection × Age 45+	0.05*	0.09**	0.01
	(0.03)	(0.04)	(0.04)
Controls			
Test score	X	X	X
Favorite subject	X	X	X
Education	X	X	X
Observations	4,976	2,472	2,504
R^2	0.02	0.03	0.02

*Notes: This table shows coefficient estimates from OLS regressions. The dependent variable is the within-candidate difference in standardized willingness to apply under a blind process and standardized willingness to apply under a non-blind process. Willingness to apply values are standardized over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. Column (1) shows the pooled results of candidates' demand for blind applications. Column (2) restricts the sample to candidates who are randomly assigned to a rejection with a non-blind application. Column (3) restricts results to candidates rejected with a blind application. All regressions include fixed effects for test scores, favorite subject, and level of education. Clustered standard errors at the candidate level are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table 4. Recruiter Decisions

Dependent variable:	Willingness to hire (standardized)							
	Non-blind				Blind			
	All	Score: 0	Score: 1	Score: 2	All	Score: 0	Score: 1	Score: 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Women	-0.06**	-0.05	0.01	-0.20***				
	(0.03)	(0.04)	(0.05)	(0.07)				
Age 45+	-0.05	0.03	-0.11*	-0.05				
	(0.03)	(0.04)	(0.06)	(0.07)				
Resume score: 1	0.52***				0.54***			
	(0.04)				(0.04)			
Resume score: 2	1.14***				1.18***			
	(0.05)				(0.05)			
STEM	0.43***	0.30***	0.51***	0.51***	0.53***	0.40***	0.70***	0.50***
	(0.05)	(0.06)	(0.08)	(0.10)	(0.04)	(0.05)	(0.07)	(0.09)
Social sciences	-0.00	0.03	-0.05	0.05	0.04	0.02	0.10	0.01
	(0.03)	(0.04)	(0.06)	(0.08)	(0.03)	(0.04)	(0.06)	(0.09)
Bachelor's degree	0.25***	0.16***	0.29***	0.30***	0.30***	0.23***	0.37***	0.30***
	(0.04)	(0.05)	(0.07)	(0.08)	(0.04)	(0.05)	(0.06)	(0.09)
Advanced degree	0.35***	0.26***	0.45***	0.28***	0.40***	0.34***	0.45***	0.41***
	(0.04)	(0.05)	(0.07)	(0.09)	(0.04)	(0.05)	(0.06)	(0.10)
Controls								
Recruiter gender	X	X	X	X	X	X	X	X
Recruiter age	X	X	X	X	X	X	X	X
Recruiter race/ethnicity	X	X	X	X	X	X	X	X
Recruiter favorite subject	X	X	X	X	X	X	X	X
Recruiter education	X	X	X	X	X	X	X	X
Observations	2,812	1,031	992	789	2,889	1,096	1,001	792
R^2	0.29	0.12	0.18	0.11	0.31	0.15	0.20	0.09

*Notes: This table shows coefficient estimates from OLS regressions, where the dependent variable is standardized recruiter willingness to hire. We standardize over the full distribution of all willingness to hire observations, pooling over the five price-lists faced by recruiters. Columns (1) to (4) show results for recruiters randomly assigned to evaluate non-blind applications, whereas columns (5) to (8) show results for recruiters randomly assigned to evaluate blind applications. Columns (1) and (5) show pooled results, whereas columns (2) to (4) and (6) to (8) present regression results by candidate sample test score (0, 1 or 2 out 2) shown to recruiters. All regressions include fixed effects for recruiter gender, age, race or ethnicity, favorite subject, and level of education. Clustered standard errors at the recruiter level are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table 5. Comparing Outcomes under Blind and Non-Blind Hiring Processes

	Top scores	Random	Blind	Non-Blind
Panel A. Tight market (# of positions = 264)				
Average score	7.55	4.21	5.95	5.86
Share women	39%	53%	37%	33%
Share 45+	41%	52%	46%	45%
Panel B. Intermediate market (# of positions = 1,015)				
Average score	5.96	4.21	4.94	4.89
Share women	48%	53%	45%	43%
Share 45+	47%	52%	51%	49%
Panel C. Slack market (# of positions = 2,067)				
Average score	4.72	4.21	4.35	4.34
Share women	52%	53%	51%	50%
Share 45+	51%	52%	50%	50%

Notes: The table presents the average technical test score among hired candidates, the share of women among hired candidates, and the share of individuals 45 or older among hired candidates under different scenarios. The top panel simulates outcomes when 264 candidates are hired; the middle panel simulates outcomes when 1,015 candidates are hired; the bottom panel simulates outcomes when 2,067 candidates are hired. "Top Scores" corresponds to a simulated hiring process where the X candidates with the best technical test scores are hired. "Random" corresponds to a simulated hiring process where X candidates are hired at random from the full pool of candidates. "Blind" corresponds to a simulated hiring process where the X candidates with the greatest hiring probability according to recruiter hiring decisions and candidate application decisions in the pre-rejection Blind treatment are hired. "Non-blind" corresponds to a simulated hiring process where the X candidates with the greatest hiring probability according to recruiter hiring decisions and candidate application decisions in the pre-rejection non-blind treatment are hired.

Table 6. Predictors of Candidates' Preferences for Blind Applications

Dependent variable:	Stated preference for blind applications						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Women	0.64***	0.17***	0.80***	0.76***	0.72***	0.60***	0.30***
	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
Age 45+	0.32***	-0.07	0.23***	0.29***	0.29***	0.32***	-0.02
	(0.07)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
Signaling		-0.98***					-0.81***
		(0.03)					(0.03)
DEI			-0.43***				-0.00
			(0.03)				(0.03)
Screening				-0.42***			-0.12***
				(0.03)			(0.03)
Identity					-0.59***		-0.24***
					(0.03)		(0.03)
Competence						0.20***	0.18***
						(0.03)	(0.02)
Controls							
Test score	X	X	X	X	X	X	X
Favorite subject	X	X	X	X	X	X	X
Education	X	X	X	X	X	X	X
Observations	2,488	2,488	2,488	2,488	2,488	2,488	2,488
R^2	0.06	0.42	0.15	0.15	0.23	0.08	0.47

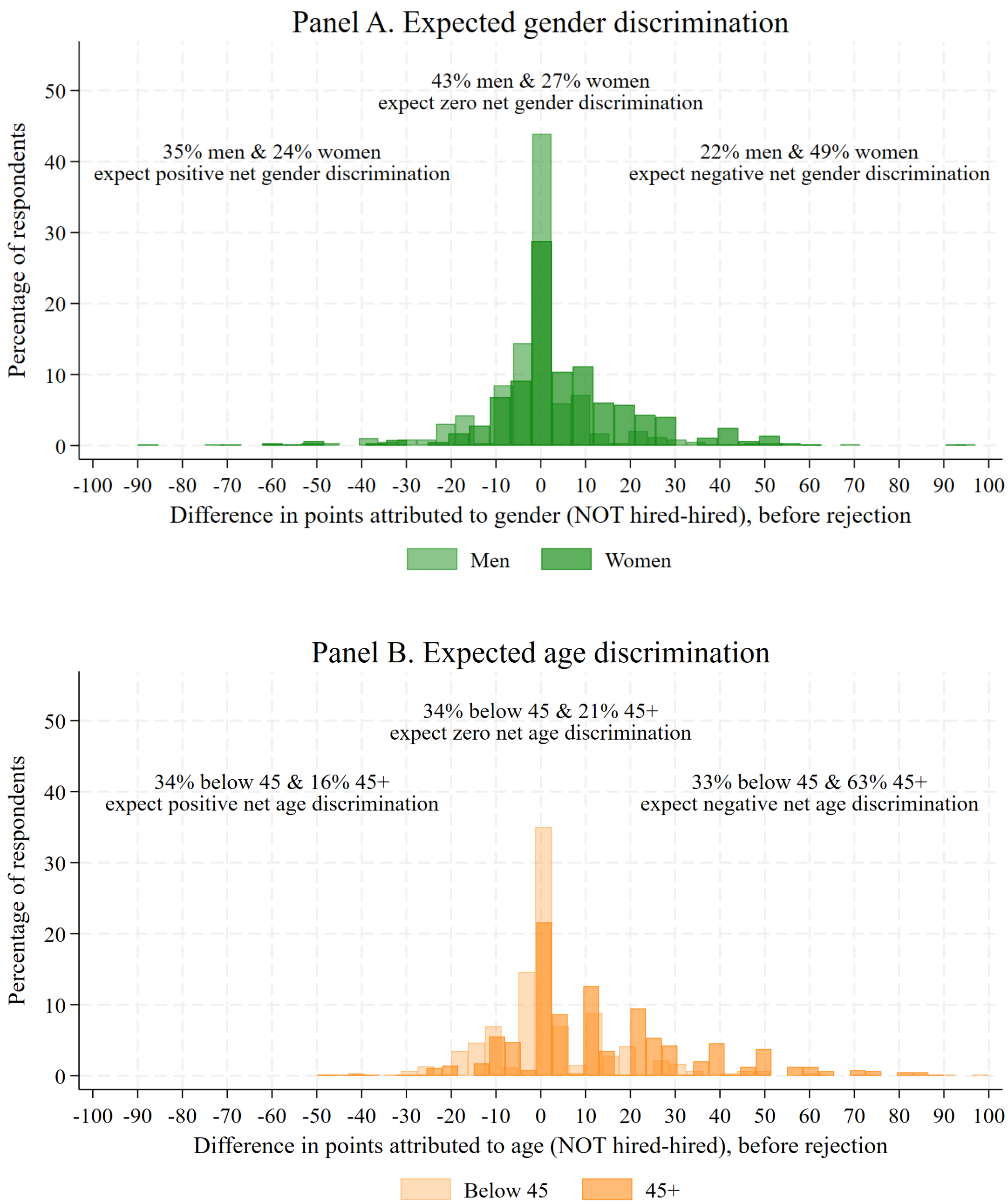
Notes: Candidates provided their stated preference for blind applications by answering the following question: "In general, when you apply for jobs, would you prefer for recruiters to be able to see your demographic characteristics, such as your gender, age, and race, or would you prefer they not have access to this information in your application?" (seven-point Likert scale from "Strongly prefer recruiters able to see my demographic characteristics (1)" to "Strongly prefer recruiters NOT able to see my demographic characteristics (7)"). Mean stated preference for blind applications is equal to 4.64. We asked the following questions to candidates, who could answer on a five-point Likert scale, from "Strongly disagree" (1) to "Strongly agree (5).

- *Signaling: "Including my demographic characteristics will help me get an interview."*
- *DEI: "Including my demographic characteristics supports diversity, equity, and inclusion in the workplace."*
- *Screening: "Including my demographic characteristics allows me to filter out discriminating employers, with whom I'd rather not have an interview anyway."*
- *Identity: "Including my demographic characteristics allows me to show a part of my identity that I'm proud of."*
- *Competence: "Including my demographic characteristics creates a doubt for me whether the recruiter selected me for my competence rather than my identity."*

*Coefficient estimates are from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, and * p<0.1.*

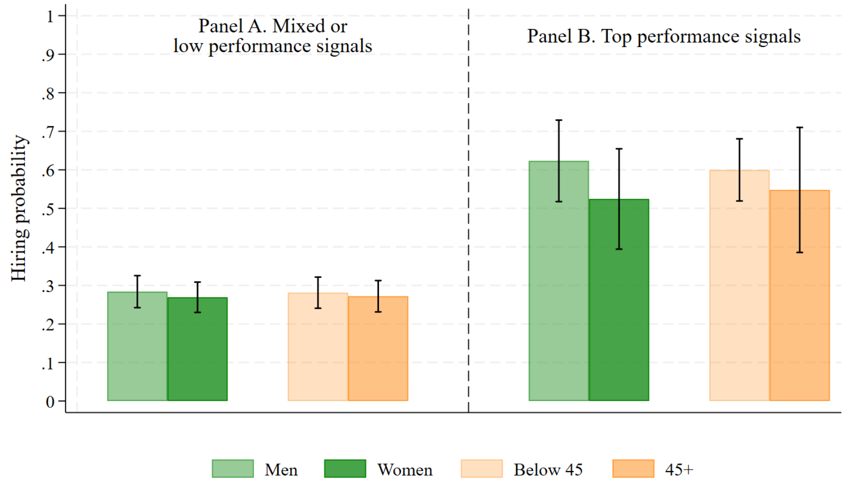
A Additional Figures and Tables

Figure A1. Candidates' Expected Gender and Age Discrimination Before Rejection



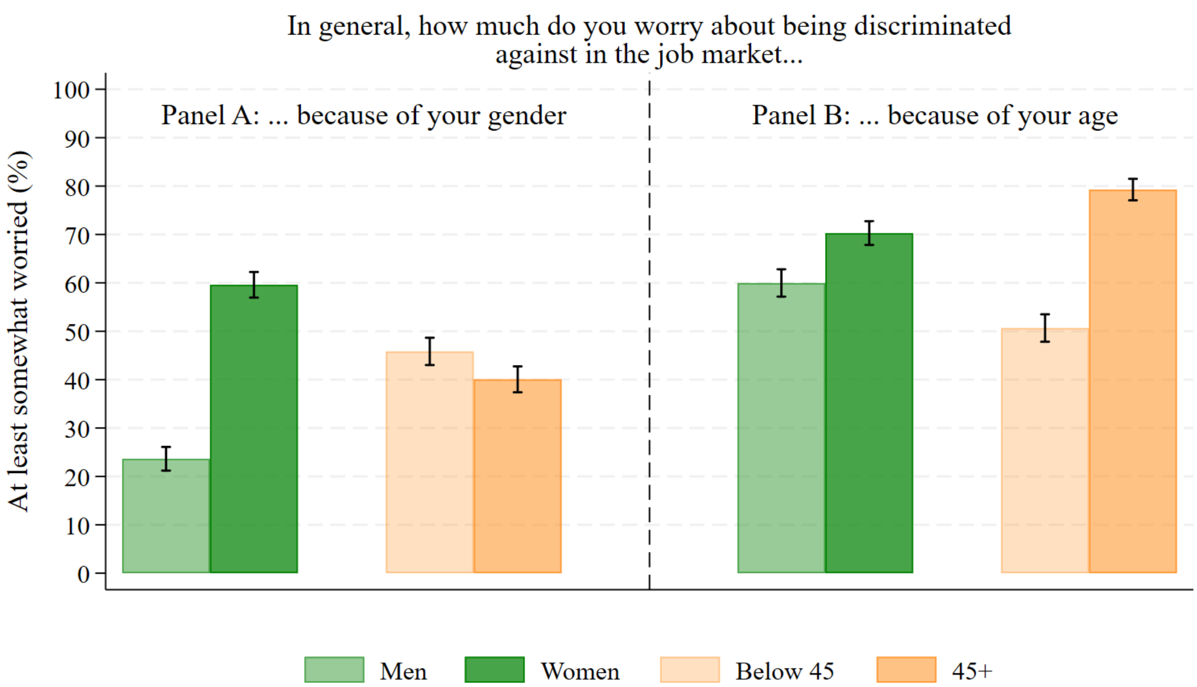
Notes: After they completed the initial two price lists, we asked the following question to candidates, based on the randomly selected resume: "Imagine that a recruiter saw this resume and decided to hire you. How much do you think the different resume components influenced the recruiter's decision? Please distribute 100 points across these components. (...) Assign more points to components that you believe had a greater impact and fewer points to those with less impact." Then, we asked: "Now, imagine that a recruiter saw this resume and decided NOT to hire you. How much do you think the different resume components influenced the recruiter's decision?" To measure expected level of gender or age discrimination, we calculate the difference between the points candidates attribute to gender or age as reasons why they would NOT be hired minus why they would be hired. This figure shows the distribution of candidates' answers, in the non-blind treatment, for expected gender discrimination (Panel A) and age discrimination (Panel B).

Figure A2. Recruiters' Hiring Probabilities, Non-Blind Applications



Notes: Bars represent recruiters' mean probabilities of hiring candidates in the non-blind resume treatment, by candidate gender and age. Panel B shows hiring probabilities for resumes with top performance signals, that is, STEM and a sample test score of 2 out 2. Panel A shows the mean probabilities for candidates with other scores and from non-STEM fields. Whiskers mark 95% confidence intervals.

Figure A3. Candidates' Perception of Discrimination in the Broader Labor Market



Notes: At the end of the survey, we asked candidates about their experiences of discrimination and their preferences regarding blind application processes in the labor market. This figure shows the share of respondents who answered that they were at least somewhat worried "about being discriminated against in the job market" because of their gender (Panel A) or age (Panel B). Respondents were asked to provide an answer on a seven-point Likert scale, from "Not at all worried" (1) to "Absolutely worried" (7), with "Somewhat worried" being a (3).

Table A1. Characteristics of Survey Respondents

	Pooled	By gender		T-test	By age		T-test
		Men	Women	*p*-value	Below 45	45+	*p*-value
Panel A. Recruiters							
Gender							
Women	0.54				0.49	0.60	0.00
Men	0.44				0.49	0.39	0.00
Other	0.02				0.03	0.01	0.03
Age 45+	0.40	0.35	0.45	0.00			
Race							
White	0.74	0.73	0.76	0.29	0.69	0.82	0.00
Black	0.14	0.14	0.15	0.66	0.15	0.12	0.16
Asian	0.10	0.10	0.09	0.39	0.13	0.05	0.00
Hispanic	0.09	0.10	0.07	0.03	0.11	0.05	0.00
Other	0.06	0.06	0.05	0.20	0.08	0.03	0.00
Level of education							
High school	0.36	0.36	0.35	0.85	0.35	0.36	0.62
Bachelor's	0.46	0.44	0.47	0.25	0.48	0.42	0.04
Advanced	0.18	0.20	0.17	0.21	0.17	0.21	0.04
Favorite subject							
Humanities	0.28	0.17	0.37	0.00	0.27	0.30	0.21
Social sciences	0.34	0.29	0.38	0.00	0.33	0.36	0.31
STEM	0.38	0.54	0.25	0.00	0.40	0.34	0.03
Observations	1,217	549	639		731	486	
Panel B. Candidates							
Women	0.53				0.52	0.55	0.20
Age 45+	0.52	0.50	0.53	0.20			
Level of education							
High school	0.35	0.36	0.34	0.49	0.37	0.33	0.02
Bachelor's	0.45	0.45	0.45	0.79	0.46	0.44	0.19
Advanced	0.20	0.20	0.21	0.63	0.17	0.24	0.00
Favorite subject							
Humanities	0.29	0.19	0.38	0.00	0.27	0.31	0.04
Social sciences	0.35	0.35	0.36	0.68	0.36	0.35	0.38
STEM	0.36	0.46	0.26	0.00	0.37	0.35	0.31
Test score	4.21	4.43	4.02	0.00	4.37	4.06	0.00
Observations	2,488	1,159	1,329		1,200	1,288	

Table A2. Randomization Balance Check

	Resume type		T-test
	Non-blind	Blind	p-value
Panel A. Recruiters			
Gender			
Women	0.53	0.54	0.76
Men	0.46	0.45	0.76
Other	0.02	0.02	0.93
Age 45+	0.40	0.40	0.87
Race			
White	0.75	0.73	0.60
Black	0.13	0.15	0.42
Asian	0.09	0.11	0.40
Hispanic	0.09	0.09	0.92
Other	0.06	0.06	0.94
Level of education			
High school	0.34	0.38	0.14
Bachelor's	0.48	0.45	0.29
Advanced	0.19	0.18	0.65
Favorite subject			
Humanities	0.28	0.28	0.87
Social sciences	0.34	0.34	0.96
STEM	0.38	0.38	0.92
Observations	597	620	
Panel B. Candidates' first resume			
Women	0.53	0.54	0.40
Age 45+	0.51	0.53	0.45
Level of education			
High school	0.33	0.37	0.03
Bachelor's	0.47	0.43	0.03
Advanced	0.20	0.20	0.88
Favorite subject			
Humanities	0.29	0.29	0.71
Social sciences	0.37	0.34	0.09
STEM	0.34	0.37	0.18
Test score	4.24	4.19	0.51
Observations	1,212	1,276	
Panel C. Candidates' rejection resume			
Women	0.52	0.55	0.25
Age 45+	0.51	0.52	0.64
Level of education			
High school	0.35	0.35	0.72
Bachelor's	0.44	0.46	0.23
Advanced	0.21	0.19	0.29
Favorite subject			
Humanities	0.29	0.29	0.65
Social sciences	0.37	0.34	0.10
STEM	0.34	0.37	0.22
Test score	4.31	4.12	0.01
Observations	1,236	1,252	

Table A3. Average Willingness to Hire and Willingness to Apply, by Resume Type

	Resume type		T-test
	Non-blind	Blind	p-value
Panel A. Initial willingness to apply			
Candidate gender			
Women	29.9	32.3	0.03
Men	38.7	39.2	0.66
Candidate age			
Below 45	35.8	36.9	0.34
45+	32.4	34.2	0.11
Panel B. Willingness to apply after rejection			
Candidate gender			
Women	21.7	25.6	0.00
Men	31.7	32.3	0.58
Candidate age			
Below 45	28.2	29.4	0.25
45+	24.6	28.0	0.00
Panel C. Willingness to hire			
Recruiter gender			
Women	128.5	140.4	0.02
Men	161.7	156.5	0.37
Recruiter age			
Below 45	153.7	158.3	0.36
45+	127.4	132.3	0.41

Notes: Panel A presents the recruiters' average willingness to hire candidates, according to the resume regime they were randomly assigned to (either evaluate non-blind or blind resumes). We show averages by recruiter gender and age. Panels B and C present candidates' average willingness to apply to the job opportunity, by resume type. Panel B shows averages before feedback, whereas Panel C shows averages after feedback. Column (3) reports the statistical significance of the differences between averages in non-blind and blind applications.

Table A4. OLS Predicting Beliefs about Test Performance

Dependent variable:	Believed score
	(1)
Women	-0.65***
	(0.09)
Age 45+	-0.10
	(0.09)
Controls	
Test score	X
Favorite subject	X
Education	X
Observations	2,488
R^2	0.19

*Notes: Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. "Believed score" refers to candidates' answers to the following question: "What do you think was your score on the test?" (open numerical answers). Clustered standard errors at the candidate level are in parentheses. Significance level: *** p<0.01.*

Table A5. OLS Predicting Measures of Self-Confidence

Dependent variable:	Score shown on resume			How qualified			Likelihood to be hired		
	All	Non-blind rejection	Blind rejection	All	Non-blind rejection	Blind rejection	All	Non-blind rejection	Blind rejection
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Women	-0.22***	-0.22***	-0.22***	-0.56***	-0.52***	-0.60***	-3.28***	-6.94***	0.28
	(0.03)	(0.04)	(0.04)	(0.06)	(0.09)	(0.09)	(0.88)	(1.23)	(1.25)
Age 45+	0.09***	0.07*	0.10**	0.08	0.15*	0.02	-1.40	-2.53**	-0.16
	(0.03)	(0.04)	(0.04)	(0.06)	(0.09)	(0.09)	(0.86)	(1.20)	(1.22)
Post-rejection	-0.40***	-0.42***	-0.37***	-0.10***	-0.07*	-0.14***	-6.53***	-6.81***	-6.28***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.70)	(0.98)	(0.98)
Women × Post-rejection	0.04*	0.07**	0.01	-0.01	-0.01	-0.01	-2.10**	0.87	-4.88***
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.83)	(1.13)	(1.21)
Age 45+ × Post-rejection	-0.02	0.02	-0.05	-0.07**	-0.08*	-0.06	-1.33	0.02	-2.62**
	(0.02)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.84)	(1.13)	(1.22)
Controls									
Test score	X	X	X	X	X	X	X	X	X
Favorite subject	X	X	X	X	X	X	X	X	X
Education	X	X	X	X	X	X	X	X	X
Observations	4,976	2,472	2,504	4,976	2,472	2,504	4,976	2,472	2,504
R^2	0.11	0.11	0.12	0.19	0.20	0.19	0.14	0.14	0.16

*Notes: Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. "Score shown on resume" (Columns (1) to (3)) refers to candidates' answers to the following question: "Recall that your resume includes your score on two random questions of the technical test. How many of these two questions do you think you got right?" (0, 1 or 2). "How qualified" (Columns (4) to (6)) refers to candidates' answers to the following question: "Compared to other participants, how qualified do you feel for this opportunity?" (seven-point Likert scale, from "Not at all qualified" to "Extremely qualified"). "Likelihood to be hired" (Columns (7) to (9)) refers to candidates' answers to the following question: "How likely do you think a recruiter was to hire someone with this exact resume?" (percentage points). We asked all three questions before and after feedback. Clustered standard errors at the candidate level are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table A6. OLS Predicting Initial Willingness to Apply: Controlling for Confidence and Risk Preferences

Dependent variable:	Willingness to apply (standardized)			
	Non-blind application		Blind application	
	(1)	(2)	(3)	(4)
Women	-0.24***	-0.16***	-0.16***	-0.08*
	(0.04)	(0.04)	(0.04)	(0.04)
Age 45+	-0.10***	-0.12***	-0.07*	-0.09**
	(0.04)	(0.04)	(0.04)	(0.04)
Believed test score		0.23***		0.23***
		(0.03)		(0.03)
Risk preferences		0.05***		0.04***
		(0.01)		(0.01)
Controls				
Test score	X	X	X	X
Favorite subject	X	X	X	X
Education	X	X	X	X
Observations	2,488	2,488	2,488	2,488
R^2	0.07	0.12	0.08	0.13

*Notes: This table shows coefficient estimates from OLS regressions, using only pre-rejection application decisions. The dependent variable is standardized candidate willingness to apply. We standardize over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. All regressions include fixed effects for test scores, favorite subject, and level of education. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table A7. Demand for Blind Applications: Candidates with Test Score Above Five

Dependent variable:	Difference in (standardized) willingness to apply Blind − Non-blind		
	All	Non-blind rejection	Blind rejection
	(1)	(2)	(3)
Women	0.12**	0.13	0.11
	(0.05)	(0.08)	(0.07)
Age 45+	0.02	0.05	-0.00
	(0.05)	(0.07)	(0.07)
Post-rejection	-0.07*	-0.05	-0.11**
	(0.04)	(0.06)	(0.05)
Post-rejection × Women	0.09*	0.14*	0.06
	(0.05)	(0.08)	(0.07)
Post-rejection × Age 45+	0.08	0.08	0.08
	(0.05)	(0.08)	(0.07)
Controls			
Test score	X	X	X
Favorite subject	X	X	X
Education	X	X	X
Observations	1,118	574	544
R^2	0.05	0.07	0.04

*Notes: This table shows coefficient estimates from OLS regressions. Sample is restricted to candidates who obtained a score of six or above out of ten. The dependent variable is the within candidate difference in standardized willingness to apply under a blind process and standardized willingness to apply under a non-blind process. Willingness to apply values are standardized over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. Column (1) shows the pooled results of candidates' demand for blind applications. Column (2) restricts the sample to candidates who are randomly assigned to a rejection with a a non-blind application. Column (3) restricts results to candidates rejected with a blind application. Clustered standard errors at the candidate level are in parentheses. Significance levels: ** p<0.05 and * p<0.1.*

Table A8. OLS Predicting Feelings of Disappointment and Perceptions of Fairness

Dependent variable:	Disappointment		Fair
	Anticipated	Realized	rejection
	(1)	(2)	(3)
Women	0.03	-0.09	0.29***
	(0.15)	(0.16)	(0.09)
Age 45+	0.23	0.02	-0.10
	(0.15)	(0.15)	(0.09)
Blind application	-0.46**	-0.60***	0.19*
	(0.18)	(0.19)	(0.10)
Blind application × Women	-0.09	-0.17	0.09
	(0.21)	(0.22)	(0.12)
Blind application × Age 45+	-0.03	-0.00	0.28**
	(0.21)	(0.22)	(0.12)
Controls			
Test score	X	X	X
Favorite subject	X	X	X
Education	X	X	X
Observations	2,488	2,488	2,488
R^2	0.04	0.05	0.11
Mean	4.69	4.48	5.02

*Notes: This table shows coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. The dependent variable for regression results in Column (1) is the answer to the following question: "Imagine you applied for this job with this resume and were not hired. How would you rate the disappointment or frustration you would feel on a scale from 0 to 10, where 0 is no disappointment or frustration at all and 10 is extreme disappointment or frustration?" (question asked pre-rejection). The dependent variable in regression results in Column (2) is the answer to the following question: "Having been rejected by this recruiter, how do you rate the disappointment or frustration you feel on a scale from 0 to 10, where 0 is no disappointment or frustration at all and 10 is extreme disappointment or frustration?" (question asked post-rejection). Finally, the dependent variable for the regression in Column (3) is the answer to the following question: "How fair do you feel this rejection was?" (possible answers on a seven-point Likert scale, from "Completely unfair" (1) to "Completely fair" (7)). Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table A9. OLS Predicting Willingness to Apply, Post-Rejection

Dependent variable:	Willingness to apply (standardized)		
	All applications post-rejection	Non-blind applications post-rejection	Blind applications post-rejection
	(1)	(2)	(3)
Women	-0.16***	-0.21***	-0.10*
	(0.05)	(0.05)	(0.05)
Age 45+	-0.02	-0.07	0.03
	(0.05)	(0.05)	(0.05)
Blind rejection	0.07	0.12*	0.03
	(0.06)	(0.07)	(0.07)
Blind rejection × Women	-0.17**	-0.18**	-0.16**
	(0.07)	(0.07)	(0.08)
Blind rejection × Age 45+	-0.12*	-0.10	-0.14*
	(0.07)	(0.07)	(0.08)
Controls			
Test score	X	X	X
Favorite subject	X	X	X
Education	X	X	X
Observations	4,976	2,488	2,488
R^2	0.08	0.09	0.08

*Notes: This table shows coefficient estimates from OLS regressions, using only post-rejection application decisions. The dependent variable is standardized candidate willingness to apply. We standardize over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. All regressions include fixed effects for test scores, favorite subject, and level of education. Clustered standard errors at the candidate level are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table A10. OLS Predicting Reasons that Candidates Attribute for Not Hired vs. Hired (Before Rejection)

Dependent variable:	Weight that candidate attributes to each factor				
	Gender	Age	Education	Subject	Performance
	(1)	(2)	(3)	(4)	(5)
Panel A: Non-blind rejection					
Not Hired	-0.45	0.50	-2.70**	-2.19***	4.84***
	(0.74)	(0.80)	(1.20)	(0.71)	(1.21)
Women	-0.36	-1.44**	4.60***	-0.21	-2.58**
	(0.63)	(0.57)	(1.11)	(0.81)	(1.12)
Not Hired × Women	6.81***	2.36**	-10.90***	-2.29**	4.01***
	(0.90)	(1.06)	(1.50)	(0.92)	(1.52)
Age 45+	0.42	-0.62	1.53	2.68***	-4.01***
	(0.62)	(0.56)	(1.14)	(0.80)	(1.12)
Not Hired × Age 45+	-1.55*	11.88***	-7.02***	-2.79***	-0.53
	(0.90)	(1.05)	(1.52)	(0.92)	(1.53)
Controls					
Test score	X	X	X	X	X
Favorite subject	X	X	X	X	X
Education	X	X	X	X	X
Observations	2,472	2,472	2,472	2,472	2,472
R^2	0.05	0.16	0.13	0.06	0.05
Mean hired	11.17	11.68	32.65	14.19	30.31
Mean not hired	13.49	19.51	20.65	9.38	36.97
Panel B: Blind rejection					
Not Hired			-10.02***	-1.75*	11.77***
			(1.48)	(1.00)	(1.46)
Women			-0.45	0.31	0.15
			(1.22)	(1.01)	(1.27)
Not Hired × Women			-3.72**	-2.41*	6.13***
			(1.74)	(1.24)	(1.73)
Age 45+			-1.28	2.56**	-1.27
			(1.23)	(1.00)	(1.28)
Not Hired × Age 45+			2.41	-2.18*	-0.23
			(1.75)	(1.25)	(1.74)
Controls					
Test score			X	X	X
Favorite subject			X	X	X
Education			X	X	X
Observations			2,504	2,504	2,504
R^2			0.08	0.03	0.12
Mean hired			42.14	19.42	38.44
Mean not hired			31 .35	15.22	53.43

*Notes: We asked the following question to the candidates for one of the two resumes before rejection: "Imagine that a recruiter saw this resume and decided to hire you. How much do you think the different resume components influenced the recruiter's decision? Please distribute 100 points across these components. Keep in mind that the total points must add up to 100. Assign more points to components that you believe had a greater impact and fewer points to those with less impact." Next, we asked them to "imagine that a recruiter saw this resume and decided NOT to hire you. How much do you think the different resume components influenced the recruiter's decision?" The dependent variable is the weight (pp) that candidates attribute to each of the five reasons for the non blind resume (Panel A) and three for the blind resume (Panel B). Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table A11. OLS Predicting Willingness to Apply Following Rejection, Split by Rejection Type

Dependent variable:	Willingness to apply (standardized)		
	All	Non-blind rejection	Blind rejection
	(1)	(2)	(3)
Women	-0.21***	-0.21***	-0.22***
	(0.04)	(0.05)	(0.06)
Age 45+	-0.09**	-0.06	-0.14**
	(0.04)	(0.05)	(0.05)
Post-rejection	-0.26***	-0.27***	-0.24***
	(0.02)	(0.03)	(0.03)
Women × Post-rejection	-0.02	0.07**	-0.11***
	(0.03)	(0.04)	(0.04)
Age × Post-rejection	0.02	0.04	-0.00
	(0.03)	(0.04)	(0.04)
Controls			
Test score	X	X	X
Favorite subject	X	X	X
Education	X	X	X
Observations	9,952	4,944	5,008
R^2	0.09	0.09	0.11

*Notes: Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. Clustered standard errors at the candidate level are in parentheses. Significance levels: *** p<0.01 and ** p<0.05.*

Table A12. OLS Predicting Relative Benefit of Blinding

	Benefit of Blinding
	(1)
Women	0.99***
	(0.07)
Age 45+	0.55***
	(0.07)
Controls	
Test score	X
Favorite subject	X
Education	X
Observations	2,488
R^2	0.12
Mean	4.53

*Notes: We asked the following question to candidates right after they completed their first two price lists: "We showed you two different resumes. Which one do you think a recruiter would be more likely to hire?" (seven-point Likert scale, from "much more likely non-blind" to "much more likely blind"). Coefficient estimates from OLS regression, which include fixed effects for test scores, favorite subject, and level of education. Robust standard errors are in parentheses. Significance levels: *** p<0.01.*

Table A13. Impact of Blind Applications on Willingness to Hire

Dependent variable:	Willingness to hire (standardized)				
	(1)	(2)	(3)	(4)	(5)
Blind	0.03	0.03	0.03	0.03	0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Controls					
Resume characteristics		X	X	X	X
Recruiter preferences			X		X
Recruiter characteristics				X	X
Observations	5,701	5,701	5,701	5,568	5,568
R^2	0.00	0.27	0.28	0.30	0.30

Notes: This table shows coefficient estimates from OLS regressions, where the dependent variable is standardized recruiter willingness to hire. We standardize over the full distribution of all willingness to hire observations, pooling over the five price-lists faced by recruiters. Regressions include fixed effects for resume characteristic (candidate's favorite subject, level of education and sample test score), recruiter characteristics (gender, age, race / ethnicity, favorite subject, and level of education), and recruiter preferences (altruism, risk preferences, and time preferences). Clustered standard errors at the recruiter level are in parentheses.

Table A14. Recruiter stated beliefs about candidate test scores compared to actual candidate test scores

Candidate characteristic	Mean recruiter beliefs	Mean candidate scores	Mean difference
Men	5.50	4.43	1.07
Women	5.06	4.02	1.04
Below 45	5.57	4.37	1.20
45+	4.57	4.06	0.51
STEM	7.40	4.59	2.81
Social sciences	3.87	3.97	-0.10
Humanities	3.43	4.04	-0.61
Advanced degree	6.62	4.58	2.04
Bachelor's	5.58	4.29	1.29
High school	3.33	3.91	-0.58

Notes: Mean recruiter beliefs averages recruiters' responses to the following question: "What do you think the average score on the technical test was for" each candidate possible characteristic (on a scale from 0 to 10). Mean candidate scores shows the actual performance of respondents in the candidate survey, by candidate characteristic.

Table A15. OLS Predicting Predicted Percent of Candidates Hired

Dependent variable:	Hired		
	All	Non-blind rejection	Blind rejection
	(1)	(2)	(3)
Women	-3.28***	-6.94***	0.28
	(0.88)	(1.23)	(1.25)
Age 45+	-1.40	-2.53**	-0.16
	(0.86)	(1.20)	(1.22)
Post-rejection	-6.53***	-6.81***	-6.28***
	(0.70)	(0.98)	(0.98)
Women × Post-rejection	-2.10**	0.87	-4.88***
	(0.83)	(1.13)	(1.21)
Age 45+ × Post-rejection	-1.33	0.02	-2.62**
	(0.84)	(1.13)	(1.22)
Controls			
Test score	X	X	X
Favorite subject	X	X	X
Education	X	X	X
Observations	4,976	2,472	2,504
R^2	0.14	0.14	0.16
Mean	38.74	38.45	39.02

*Notes: Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. "Hired" refers to candidates' answers to the following question: "How likely do you think a recruiter was to hire someone with this exact resume?" (percentage points). Candidates in the non-blind rejection condition were asked this question with respect to their non-blind resume. Candidates in the blind rejection condition were asked this question with respect to their blind resume. We asked this question before and after feedback. Clustered standard errors at the candidate level are in parentheses. Significance levels: *** $p<0.01$ and ** $p<0.05$.*

Table A16. OLS Predicting Candidates' Beliefs about Recruiters' Preferences

Dependent variable:	Beliefs about non-blind hiring chances of:			
	Men	Women	Younger	Older
	(1)	(2)	(3)	(4)
Women	0.39***	-0.52***	-0.01	-0.20***
	(0.04)	(0.04)	(0.04)	(0.04)
Age 45+	-0.03	0.04	0.29***	-0.30***
	(0.04)	(0.04)	(0.04)	(0.04)
Controls				
Test score	X	X	X	X
Favorite subject	X	X	X	X
Education	X	X	X	X
Observations	2,488	2,488	2,488	2,488
R^2	0.07	0.09	0.03	0.05
Mean	3.59	2.57	3.64	2.16

*Notes: We asked candidates the following questions: "Do you think that, in this study, recruiters were more likely to hire men when the resume did not include information about gender or when it did include information about gender?" We asked the same questions about the candidates' beliefs regarding women (Column (2)), younger workers (Column (3)), and older workers (Column (4)). Answers on a five-point Likert scale, from "Much more when it did not include information about gender" (or age) to "Much more when it included information about gender" (or age). Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. Robust standard errors are in parentheses. Significance level: *** p<0.01.*

Table A17. OLS Predicting Candidates' Worries about Discrimination

Dependent variable:	Discrimination worries	
	Gender	Age
	(1)	(2)
Women	1.22***	0.47***
	(0.06)	(0.07)
Age 45+	-0.27***	1.37***
	(0.06)	(0.07)
Controls		
Test score	X	X
Favorite subject	X	X
Education	X	X
Observations	2,488	2,488
R^2	0.16	0.16
Mean	2.57	3.56

*Notes: We asked candidates the following question: "In general, how much do you worry about being discriminated against in the job market because of your gender?" (Column (1)). Column (2) presents the regressions based on the same question about candidates' worry about age discrimination. Answers are on a seven-point Likert scale, from "Not at all worried" (1) "Absolutely worried" (7). Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. Robust standard errors are in parentheses. Significance level: *** p<0.01.*

Table A18. OLS Predicting Candidates' Beliefs about Benefits of Non-Blind Application Processes

Dependent variable:	Signaling	DEI	Screening	Identity	Competence
	(1)	(2)	(3)	(4)	(5)
Women	-0.47***	0.39***	0.29***	0.14***	0.15***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Age 45+	-0.39***	-0.19***	-0.06	-0.05	-0.04
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Controls					
Test score	X	X	X	X	X
Favorite subject	X	X	X	X	X
Education	X	X	X	X	X
Observations	2,488	2,488	2,488	2,488	2,488
R^2	0.10	0.04	0.02	0.03	0.01
Mean	2.53	3.14	3.23	3.09	2.97

Notes: We asked the following questions to candidates, who could answer on a five-point Likert scale, from "Strongly disagree" (1) to "Strongly agree (5).

- *Signaling (Column (1)): "Including my demographic characteristics will help me get an interview."*
- *DEI (Column (2)): "Including my demographic characteristics supports diversity, equity, and inclusion in the workplace."*
- *Screening (Column (3)): "Including my demographic characteristics allows me to filter out discriminating employers, with whom I'd rather not have an interview anyway."*
- *Identity (Column (4)): "Including my demographic characteristics allows me to show a part of my identity that I'm proud of."*
- *Competence (Column (5)): "Including my demographic characteristics creates a doubt for me whether the recruiter selected me for my competence rather than my identity."*

*Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. Robust standard errors are in parentheses. Significance level: *** p<0.01.*

Table A19. OLS Predicting Candidates' Beliefs about Benefits of Blind Application Processes

Dependent variable:	Interview non-blind (1)	No interview non-blind (2)	Applicant pool (3)	Diverse workforce (4)	Productive workforce (5)	Standard policy (6)
Women	-0.04	0.21***	0.04	0.08	0.10*	0.22***
	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)
Age 45+	-0.21***	-0.08**	-0.03	-0.02	-0.12**	0.00
	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)
Controls						
Test score	X	X	X	X	X	X
Favorite subject	X	X	X	X	X	X
Education	X	X	X	X	X	X
Observations	2,488	2,488	2,488	2,488	2,488	2,488
R^2	0.02	0.03	0.01	0.01	0.01	0.01
Mean	2.83	3.50	4.77	4.72	4.68	4.88

Notes: We asked the following questions to candidates, who could answer on a five-point Likert scale, from "A lot better if they knew my demographic information" (1) to "A lot better if they didn't know my demographic information" (5):

- *Interview non-blind (Column (1)): "Imagine being offered an interview after submitting a job application. Would you feel better about it if the recruiter chose to interview you after seeing your demographic characteristics on your resume?"*
- *No interview non-blind (Column (2)): "Imagine not being offered an interview after submitting a job application. Would you feel better about it if the recruiter chose to not interview you after seeing your demographic characteristics on your resume?"*

We asked the following questions to candidates, who could answer on a seven-point Likert scale, from "Strongly disagree" (1) to "Strongly agree (7):

- *Applicant pool (Column (3)): Blind hiring processes "lead to a more diverse applicant pool."*
- *Diverse workforce (Column (4)): Blind hiring processes "lead employers to hire a more diverse workforce."*
- *Productive workforce (Column (5)): Blind hiring processes "lead to a more productive workforce."*
- *Standard policy (Column (6)): Blind hiring processes "should be standard policy for all employers."*

*Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, and * p<0.1.*

Table A20. OLS Predicting Candidates' Preferences for Blind Applications

Dependent variable:	Preference for blind applications						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Women	0.65***	0.50***	0.63***	0.62***	0.61***	0.55***	0.48***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)
Age 45+	0.42***	0.37***	0.32***	0.32***	0.35***	0.31***	0.41***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Interview	0.48***						0.31***
	(0.03)						(0.03)
No interview		0.64***					0.48***
		(0.03)					(0.03)
Diverse pool			0.18***				0.07*
			(0.02)				(0.04)
Diverse workforce				0.15***			-0.10***
				(0.02)			(0.04)
Productive workforce					0.25***		-0.08***
					(0.02)		(0.03)
Standard policy						0.41***	0.36***
						(0.02)	(0.03)
Controls							
Test score	X	X	X	X	X	X	X
Favorite subject	X	X	X	X	X	X	X
Education	X	X	X	X	X	X	X
Observations	2,488	2,488	2,488	2,488	2,488	2,488	2,488
R^2	0.15	0.20	0.09	0.08	0.11	0.20	0.33

*Notes: We asked candidates the following question: "In general, when you apply for jobs, would you prefer for recruiters to be able to see your demographic characteristics, such as your gender, age, and race, or would you prefer they not have access to this information in your application?" (seven-point Likert scale from "Strongly prefer recruiters able to see my demographic characteristics (1)" to "Strongly prefer recruiters NOT able to see my demographic characteristics (7)"). Mean preference for blinding is equal to 4.64. See Table A19 for definitions of variables Interview, No interview, Diverse pool, Diverse workforce, Productive worforce, and Standard policy. Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, and * p<0.1.*

B Technical test

Bold answer choices indicate the correct response.

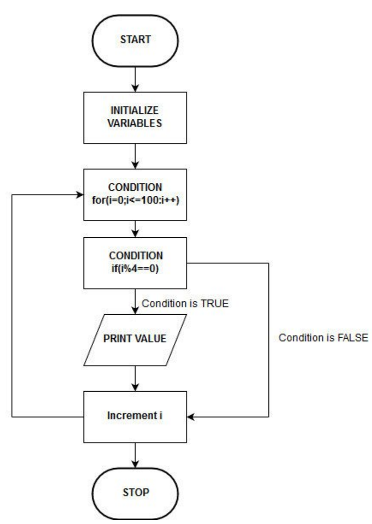
1. Data Set A: flower, cat, dog, house
   Data Set B: cat, bird, flower, door

   What values will be returned if Data Set A and Data Set B were combined by an inner join?
   A. cat, bird, flower, door
   B. cat, dog
   C. flower, cat, dog
   D. cat, flower

```
0001001001000101
0010010011101100
10101101001...
```

2. What is this code an example of?
   A. **Executable Machine code**
   B. High-level programming code
   C. Assembly code
   D. Pascal programming code

3. Consider this chart:



   What does this flow chart represent?
   A. A Boolean

B. A list

C. A composite

D. A loop

4. Consider this piece of code:

```
<script>
var x, y, z;
x = 5;
y = 6;
z = x + y;
document.getElementById("demo").innerHTML =
"The value of z is " + z + ".";
</script>
```

What is its output?

A. The value of z is x + y.

B. **The value of z is 11.**

C. x + y

D. 11

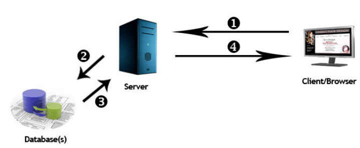
5. You are coding a new video game and have run into an issue. You want to create a main menu that allows the player to press 1 to play with only one player, to press 2 for multiplayer, or to press Q to quit the game. You would like all players to see this menu at least once at the beginning of the game. What kind of coding element is best to achieve this?

A. A for loop

B. A function with a return value but no argument.

C. A do while loop

D. A function with an argument but no return value.



6. What kind of website is depicted above?

A. Static website

B. **Dynamic website**

C. eCommerce website

D. Service provider website

7. Consider the following variable equation: k = 9

What would be the result if you were to code k != 4?

A. FALSE
B. TRUE
C. k would now equal 4
D. NA

8. Which key on a computer keyboard is used to capitalize letters?
A. Ctrl (Control)
B. Option
C. Shift
D. Windows

9. Consider this block of code:

```
if (paygrade == 7)
  if (level >= 0 && level <= 8)
    salary *= 1.05;
  else
    salary *= 1.04;
else
  salary *= 1.06;
```

If paygrade == 8 and level == 6, which will be the output?
A. salary *= 1.05
B. salary *= 1.04
C. salary *= 7
D. salary *= 1.06

10. If you want to maintain and update a database, which language is typically best to use?
A. HTML
B. C++
C. SQL
D. Go

C Resumes

Figure C1. Non-blind resumes instructions for recruiters

The Resumes

For your hiring choices, we've made simple resumes for each candidate. Each resume has this information:

Age:

Under 45 years old	45 years old and above

Gender:

Man	Woman

Educational Attainment:

High School Degree or Less	Bachelor's Degree	Advanced Degree

Favorite Subject:

Humanities (such as writing, languages, art)	Social Science (such as psychology, economics, history, philosophy)	STEM (such as science, technology, engineering, or math)

Every resume will also show the candidate's performance on the two sample questions from the technical test. Specifically, the computer randomly selected two questions for each candidate. You'll see how many of those two questions the candidate answered correctly:

Sample Performance on Technical Test:

0 out of 2 correct	1 of 2 correct	2 of 2 correct

Figure C2. Example of a non-blind resume that a recruiter was asked to evaluate

Here is your 1st resume to evaluate:

Age: **Under 45 years old**
Gender: **Man**
Educational Attainment: **Bachelor's Degree**
Favorite Subject: **STEM (such as science, technology, engineering, or math)**
Sample Performance on Technical Test: **0 of 2 correct**

Figure C3. Example of a non-blind resume that a recruiter was asked to evaluate

Resume 1 out of 5:

Educational Attainment: **High School Degree or Less**
Favorite Subject: **STEM (such as science, technology, engineering, or math)**
Sample Performance on Technical Test: **2 of 2 correct**

D Price lists

Figure D1. First rows of price list shown to recruiters

Let us know your choice for each row by clicking either **HIRE** or **DO NOT HIRE.** When you want to switch from **HIRE** to **DO NOT HIRE**, the remaining rows will automatically change to **DO NOT HIRE**. You can always change your mind, and the autofilled rows will become clickable again.

HIRE THE CANDIDATE	DO NOT HIRE
50 CENTS FOR EACH QUESTION ANSWERED CORRECTLY	50 CENTS TOTAL
50 CENTS FOR EACH QUESTION ANSWERED CORRECTLY	100 CENTS TOTAL
50 CENTS FOR EACH QUESTION ANSWERED CORRECTLY	150 CENTS TOTAL
50 CENTS FOR EACH QUESTION ANSWERED CORRECTLY	200 CENTS TOTAL
50 CENTS FOR EACH QUESTION ANSWERED CORRECTLY	250 CENTS TOTAL
50 CENTS FOR EACH QUESTION ANSWERED CORRECTLY	300 CENTS TOTAL
50 CENTS FOR EACH QUESTION ANSWERED CORRECTLY	350 CENTS TOTAL

Note: "Do not hire" column increases by increments of 50 cents up to 1050 cents.

E Sample selection

This section describes our sample restrictions, which we pre-registered on May 13th, 2024 (AEARCTR-0011771).

Lack of attention is a common problem with online survey experiments (Boring and Delfgaauw, 2024; Haaland et al., 2023; Peer et al., 2022; Stantcheva, 2022). Our survey includes attention checks, understanding questions, and timers to allow us to detect inattentive respondents.

We pre-registered that we would exclude respondents who did not pay enough attention to instructions and who provided arbitrary answers, especially on the price lists. We want to make sure that respondents spend enough time thinking about the questions and do not rush through the survey. We also want to make sure that our respondents understand the instructions correctly. In order to detect respondents who are inattentive or do not understand the questions properly, we include different checks throughout the survey. We pre-registered a series of restrictions in order to increase our chances of a high quality sample. As pre-registered, a respondent must pass each restriction in order to be included in our final sample.

E.1 Attention Checks

We include attention questions in both recruiter and candidate surveys, as suggested by Haaland et al. (2023). In both surveys, we ask: "The next question is about the following problem. In questionnaires like ours, sometimes there are participants who do not carefully read the questions and just quickly click through the survey. This means that there are a lot of random answers which compromise the results of research studies." To recruiters, we then ask "To show that you read our questions carefully, please enter twenty as your answer to the following question. How many resumes did you just evaluate?" To candidates, we ask "To show that you read our questions carefully, please enter twenty as your answer to the following question. How many different resumes did we show you?" We exclude from our final sample any respondent who does not answer this question correctly (we accept typos).

E.2 Understanding Questions

We also include questions to measure whether respondents understand basic instructions. Respondents must answer correctly in order to continue, but they have the opportunity to modify their answer if they fail to provide a correct answer. However, we exclude from our final sample any respondent who did not answer the understanding question correctly the first time.

E.3 Dominated Choices

In the lists in both surveys, we added strictly dominated choices to check whether respondents provide reasonable responses. For recruiters, the maximum payment they can receive when hiring the candidate is 500 cents (in case candidates answered all ten test questions correctly). A recruiter who understood the list instructions correctly should not provide a willingness to hire above that threshold. For recruiters, we allow one mistake (that is, one willingness to hire answer above 500 across their five resumes evaluated), but we exclude from analysis the evaluation that contains that error. A recruiter submits two or more willingness to hires above 500 cents is excluded fully from the sample. For candidates, the highest price at which a money-maximizing candidate would be willing to apply is 100 cents. We exclude any candidate whose willingness to apply is above that threshold on any of their four price lists.

E.4 Reading Time

Finally, we measure how much time participants spend on each instruction page. We exclude from the sample any respondent who does not spend sufficient time reading the most important instructions. To determine a reasonable threshold, we use findings from research in reading and cognitive psychology that highlights the trade-off between speed and accuracy in reading. This research estimates that the average silent reading speed for English readers of non-fiction is around 250 words per minute, and that thorough comprehension drops past two or three times that reading speed (Brysbaert, 2019; Rayner et al., 2016). Qualtrics states the average human reading speed is 300 words per minute and uses this speed to estimate the survey duration.[22] We restrict our final sample to those respondents measured to have a reading speed of no more than 400 words per minute on the main instructions pages that describe the multiple price lists.[23]

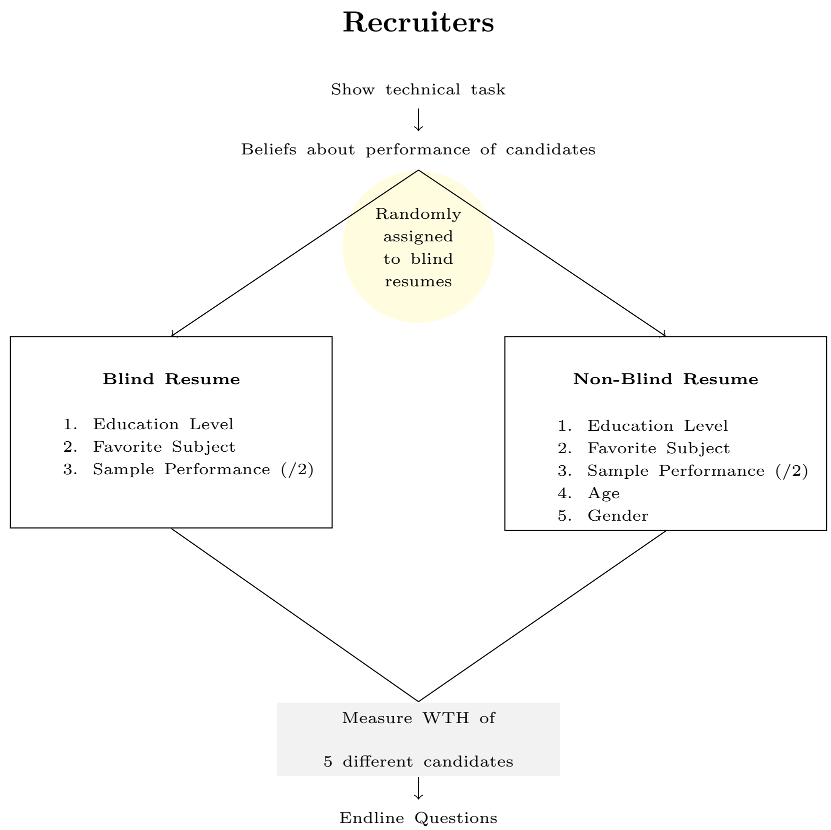
Table E1. Percentage of respondents who fail the different checks

Test	Recruiter survey	Candidate survey
Attention check	8.6%	8.0%
Comprehension check	4.2%	8.2%
Coherence test	26.5%	5.7%
Instruction reading time	28.5%	24.9%
Failing at least one test	**51.3%**	**37.5%**
N	*2,501*	*3,992*

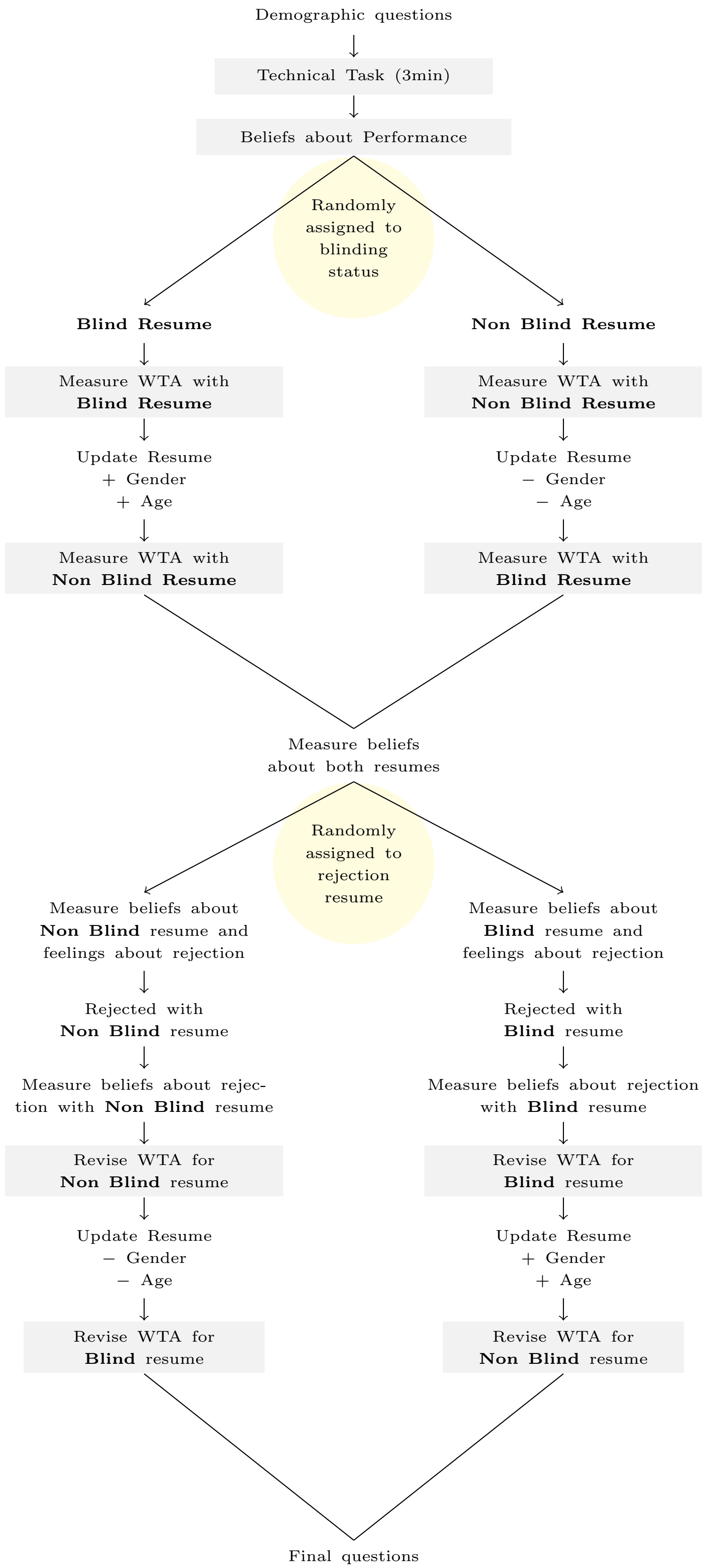
[22] https://www.qualtrics.com/support/survey-platform/survey-module/survey-checker/survey-methodology-compliance-best-practices/.

[23] For recruiters, we require a time spent of at least 40 seconds on the price list instructions page that includes 266 words. For candidates, we require a time spent of at least 36 seconds on the price list instructions page that includes 242 words.

F Experimental Design



Candidates


Demographic questions
Technical Task (3min)
Beliefs about Performance
Randomly assigned to blinding status
Blind Resume
Non Blind Resume
Measure WTA with Blind Resume
Measure WTA with Non Blind Resume
Update Resume + Gender + Age
Update Resume − Gender − Age
Measure WTA with Non Blind Resume
Measure WTA with Blind Resume
Measure beliefs about both resumes
Randomly assigned to rejection resume
Measure beliefs about Non Blind resume and feelings about rejection
Measure beliefs about Blind resume and feelings about rejection
Rejected with Non Blind resume
Rejected with Blind resume
Measure beliefs about rejection with Non Blind resume
Measure beliefs about rejection with Blind resume
Revise WTA for Non Blind resume
Revise WTA for Blind resume
Update Resume − Gender − Age
Update Resume + Gender + Age
Revise WTA for Blind resume
Revise WTA for Non Blind resume
Final questions