Discrimination, Rejection, and Willingness to Apply: Effects of Blind Hiring Processes *

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ABSTRACT

We investigate how candidates' willingness to apply responds to (potential) discrimination and rejection using a simulated labor market. 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 the interconnected nature of recruiter and candidate decision-making.

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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? We focus in particular on how blinding impacts responses to negative feedback. 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?

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.[1] Together, we are able to study how both the demand for and supply of candidates is shaped by blinding the evaluation process, both initially and after negative feedback.

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

[1] We tell Prolific participants that "we're exploring job search dynamics" and that they will "play the role" of a job candidate or of a recruiter.

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 compared to other candidates with the same resume; the discrimination seems to be concentrated among top performers.

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.[2] 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. 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. And, on average, both younger and older individuals are more willing to apply under a blind hiring than a non-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.

A key advantage of our context is that we can then explore how candidate behavior evolves after negative feedback. 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 (education, field of study, or sample performance, and in the

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

non-blind rejection treatment, age or gender). Then, we explore how they revise their likelihood of being hired both under blind and non-blind regimes, and 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 by women and older individuals. While the willingness to apply of men and younger individuals 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.

Negative feedback also has 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.

Because we have data on both sides of the market, we can examine net market outcomes under both a blind and non-blind regime and under a variety of counterfactuals. 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 paper expands the discussion of the policy effectiveness of blind application procedures by bringing together evidence on both supply-side and demand-side effects. From a demand-side perspective, natural and field experiments have investigated the impacts of blinding on recruiter discrimination against counter-stereotypical candidates (Åslund and Skans, 2012; Krause et al., 2012; Neumark, 2024; Blommaert and Coenders, 2024; Parodi et al., 2024; Chang and Chang, 2025). Our additional data on candidate productivity allows us to not only document how discrimination alters the representation of stereotyped candidates under non-blind hiring procedures, but also to explore the efficiency of hiring under both blind and non-blind procedures.[3]

Our paper also contributes to a growing literature that explores how candidates anticipate and respond to the possibility of discrimination. Recent experiments with online samples suggest that negatively stereotyped candidates may also prefer blind hiring or promotion processes due to concerns about the possibility of discrimination. For instance, Alston (2019) finds evidence 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. Consistent with this idea, Charness et al. (2020) report that women are more likely to choose avatars that mask their gender when applying for stereotypically male-typed tasks. Similarly, in a study on algorithmic hiring, Avery et al. (2024) finds that AI-assisted processes increase the proportion of female candidates that complete an application for a male-dominated tech job. Controlled experiments have also shown an impact of anticipated or experienced discrimination on worker effort. Gagnon et al. (2025) show that women reduce labor supply on the intensive margin when informed that they are paid less than men for performing the same task. Similarly, Ruebeck (2024) finds that when female workers believe there is more discrimination in promotion decisions, they demand higher wages to continue working. There is also evidence that the psychological cost associated with experienced discrimination further motivates candidates to avoid non-blind applications (Ruebeck, 2024; Ridley,

[3]Uchida (2025) conducts a similar analysis using data from a field experiment randomizing the evaluation mode for conference paper submissions, relying on data on future citations and impact to estimate paper quality.

2025). 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. This has been found both in controlled experiments (Kang et al., 2016; Kudashvili and Lergetporer, 2022; Aksoy et al., 2023) and in natural field environments (Zussman, 2013; He et al., 2024).[4]

Of course, while some candidates anticipate discrimination, others may expect it to work in their favor. This can be due to statistical discrimination (Phelps, 1972; Arrow et al., 1973; Aigner and Cain, 1977), 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 are more likely to apply, and Behaghel et al. (2015) show 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 and real) discrimination impacts labor market matching and on-the-job productivity. Goldsmith et al. (2004) were the first to propose a theory linking perceived discrimination to labor supply through psychological channels and provide correlational evidence that women who believe they have been discriminated against in job search subsequently work less, while such perceptions have no significant effect on male labor supply. Glover (2024) shows that perceived recruiter discrimination impacts the job search intensity of minorities. Similarly, 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., 2026), and Glover et al. (2017) show that minority grocery store employees perform worse on-the-job when managed by more implicitly biased supervisors. Ruebeck (2024) also 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,

[4]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).

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 several explanations for demand for non-blind versus blind applications. 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., 2025), 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 Motivating Evidence

Before describing our design and formalizing our hypotheses, we present descriptive evidence from administrative data suggesting that demand for blinding may be a quantitatively important and heterogeneous phenomenon in real labor markets. This research project originated from an initial collaboration with the French Public Employment Service (PES) who aimed to design programs and services addressing the effect of perceived discrimination on labor supply at the application stage. We obtained data for more than 100,000 vacancies that were linked to roughly 1.3 million applications through a, now defunct, service called *telecandidature*. It offered a quick, CV-less process in which job-seekers could apply to openings and, crucially, could choose whether their name would be revealed to the recruiter in the initial application. The *telecandidature* platform was available for roughly 17% of all vacancies posted with the PES during the panel available to us in 2014-2015.[5]

On average, approximately 20% of candidates authorize the release of their name to the recruiter at this initial application stage, with interesting heterogeneity by gender and occupation. When comparing men and women applying to the *same* job, there are significant gender gaps that vary substantially across occupations. While women are about 2 percentage points more likely to reveal their name overall, Panel A of Figure A1 shows that the within-vacancy gender gap can have different signs and exhibits significant heterogeneity in magnitude. Panel B shows how the probability to blind the initial employer contact evolves for each successive application for the *same* candidate. For both male and female candidates, the rate of blinding one's name increases steeply over the first several applications conditional on candidate fixed effects. Panel C illustrates how the estimated gender gap (Female - Male) evolves dynamically. We see that female candidates initially increase their blinding rate more than male candidates compared to the initial application but that the trend inverses. Around the candidate's 10th *telecandidature*, we observe that women become less and less likely to blind their name compared to men. It thus appears that preferences for blinding may change over the unemployment spell as its perceived private returns evolve. This suggests that sensitivity to rejections or beliefs about employer discrimination can also evolve dynamically.

While this evidence suggests that demand for blinding may be a potentially important channel

[5] See Glover (2024) for more details on the process and the institutional setting.

governing labor supply in a representative market, these field data are insufficient for identifying causal mechanisms. This motivates a controlled experiment in which applying with a blind or non-blind application is an explicit, randomized choice, isolated cleanly from other features of the job opening. Our experimental design allows us to causally identify the impact of blinding on application decisions, cleanly isolate the mechanisms, and does so for a computer coding task – a technical domain in which gender stereotypes may be particularly top of mind.

3 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.

3.1 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.

3.1.1 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.

3.1.2 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.[6] 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 Appendix C.

3.1.3 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 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

[6] We only 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.

to "Hire" a given candidate as their willingness to hire that candidate.[7] Appendix D 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 hired candidates earning more in expectation.

3.1.4 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

[7] 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.

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, after showing the test questions, and prior to resume evaluations.[8]

3.1.5 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.

3.2 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.

3.2.1 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).[9] At this stage of the

[8]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.

[9]Candidates who identify as non-binary/third gender or other are excluded from our final sample for analysis, as pre-registered. These participants were only shown their blind resume and completed price lists—before and after rejection—based on the blind resume.

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.

3.2.2 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.

3.2.3 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.

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.[10] If the recruiter did not choose

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

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 five 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 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.[11]

Candidates assigned to see the Blind (Non-Blind) treatment first are shown their Blind (Non-

[11] 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.

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.

3.2.4 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.[12]

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 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

[12] 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."

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.

3.2.5 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.

3.2.6 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.

3.2.7 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.

3.2.8 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 do not ask 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.

3.3 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 receive $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.[13]

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. We present the distribution of test scores by gender and age groups in Figure 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.

4 Hypotheses

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

[13]Our payments and stakes are in line with standard practices of social science experiments on Prolific. One common concern with online experiments is whether stakes are sufficiently high to engage participants and elicit meaningful data. While we cannot know how our results might differ in higher stakes environments, we are somewhat reassured that our relatively lower stakes seem more likely to lead to noisier data, pushing against finding differences in behavior across treatments and gender. Furthermore, across many contexts, evidence from relatively low stakes laboratory and online experiments has proven to have relevance for understanding field contexts of interest (Falk and Heckman, 2009; Niederle, 2025; Roth, 2010). Thus, while additional field research is needed to better understand the implications of our findings for behavior in labor markets, we believe that working in a highly controlled environment, albeit with smaller stakes, has the potential to deliver important insights.

4.1 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.

4.2 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.[14]

4.3 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.

5 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.

[14]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.

5.1 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). Our pre-registered within-subject analysis – in which each candidate completes price lists under both a blind and a non-blind application process – isolates an economically-relevant estimand. Labor markets exhibit increasingly diverse application channels through which workers and firms match. In choosing an application channel, like blind or non-blind, candidates evaluate each option relative to their own outside option.

To ease interpretation, we present the effects in standard deviation units.[15]

5.1.1 Gender and Age Differences in Willingness to Apply

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 0.21 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 0.09 SDs. Gender and age gaps are approximately 25% smaller under a blind application process ($p < 0.01$ for the reduction in the gender gap, $p \approx 0.29$ for the reduction in the age gap).[16]

An interesting question is whether we find similar estimates when using only between-candidate variation. In Appendix Table A5, we present a replication of Table 1 using only observations from the first application choices individuals made. This represents a different estimand: rather than measuring how the *same* candidate adjusts her willingness to apply when moving between blind and non-blind channels, it compares willingness to apply across different candidates who were randomly assigned to different initial conditions, i.e. not how the option of blinding changes this person's application behavior.

[15] 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.

[16] For simplicity, our main text presents specifications that analyze the independent impacts of gender and age on willingness to apply. In the Appendix, we present additional analysis that explores their interaction, estimating effects separately for young men, young women, older men, and older women. Appendix Table A4 presents a replication of Table 1 using this approach.

The across-subject comparison confounds any blinding effect with individual-level heterogeneity in willingness to apply, heterogeneity that, in our data, accounts for over 90% of the total variance in application decisions. As a consequence, we observe standard errors on the blinding coefficients that are 3.4-3.7 times larger. The across-subject estimates do still yield a significant gender gap in non-blind willingness to apply (-0.20 SDs, $p < 0.01$), consistent with its large magnitude relative to the across-subject MDE of 0.16 SDs, but the blinding effects and their interactions are not statistically distinguishable from zero.[17]

We then 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 0.56 points worse than men ($p < 0.01$, see Appendix Table A6). We find similar gender gaps across our other proxies for confidence (see Appendix Table A7).

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 0.56 points worse than men ($p < 0.01$, see Appendix Table A6). We find similar gender gaps across our other proxies for confidence (see Appendix Table A7). Interestingly, we do not see a similar self-stereotyping gap in terms of age. Conditional on technical test score and other resume characteristics, there is no age gap in believed total test score or in other proxies for confidence (see Appendix Table A6 and A7). In our setting, self-stereotyping seems much more relevant for understanding gender differences than age differences.[18]

[17] The across-subject minimum detectable effect for the Blind$\times$Woman interaction is 0.22 SDs - more than three times the 0.064 SD effect we estimate within-subject – implying only 13% power to detect this interaction at conventional significance levels. Detecting this interaction across-subject with 80% power would require approximately 30,000 candidates, roughly twelve times our sample. Equivalently, detecting women's 0.07 SD demand for blinding as a combined effect across-subject with 80% power would require approximately 18,000 candidates.

[18] 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 A8 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, consistent with the possibility of anticipated discrimination being an additional driver in this treatment, a hypothesis we explore directly in the sections that follow.

5.1.2 Initial Demand for Blinding

We refer to the difference in an individual's willingness to apply under a blind process relative to a non-blind process as their revealed demand for blind applications. Column 1 of Table 1 reveals no demand for blind applications among young men (coefficient of 0.01 on Blind). But, we estimate that women's demand for blinding is 0.07 SDs, significantly greater than 0 ($p < 0.01$), and significantly greater than men's (by 0.06 SDs, $p < 0.01$). Average demand for blinding among older individuals is weakly positive, but not significantly different than 0 or significantly different than demand for blinding among younger 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. 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.[19] More formally, Appendix Table A9 explores heterogeneity in the demand for blinding by technical test score using regression analysis, estimating that every 1-point increase in technical test score increases demand for blinding by 0.02 SDs ($p < 0.01$). Finally, we can also explore whether blinding helps to more efficiently sort the candidates on quality, by correlating WTA and candidate quality, as proxied by technical test score, under blind compared to non-blind processes. We observe a stronger positive correlation under blind applications (0.20) than non-blind applications (0.17).

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 blind 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 A10. Women report a significantly greater anticipated benefit to blind applications compared to men, by a full point ($p < 0.01$); older individuals also anticipate significantly greater

[19]For a more granular presentation, Appendix Figures A8 and A9 show willingness to apply by treatment and test scores.

benefits to blinding than younger individuals (by 0.55 points, $p < 0.01$).[20]

We also ask individuals directly about how they believe their gender (age) will factor into hiring decisions for non-blind applications. Figure A3 shows that women (older individuals) are more likely to anticipate that their gender (age) reduces their likelihood of being hired. Appendix Table A11 shows the predictors of anticipated gender and age discrimination, both before rejection (Columns 1 and 2) and after (Columns 3 and 4). As expected, women are significantly more likely than men to anticipate gender discrimination ex-ante and perceive it as a factor in their rejection ex-post; older individuals are significantly more likely than younger individuals to anticipate age discrimination ex-ante and perceive it as a factor in their rejection ex-post. Perhaps more interestingly, we also see evidence consistent with the link between overconfidence and perceived bias proposed by Heidhues et al. (2025). Conditional on measured test scores, we see that an individual's believed test score, a proxy for their confidence, is strongly predictive of how much discrimination they perceive against their type.

These beliefs map into their application decisions. Figure 3 shows that candidates who anticipate discrimination against their type reveal significant 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. Table 2 formalizes this analysis, predicting an individual's WTA from their beliefs about discrimination against their type. Column 1 predicts pre-rejection willingness to apply, adding to the regression anticipated net gender discrimination against their type and anticipated net age discrimination against their type. We see that the extent of anticipated discrimination predicts an individuals' willingness to apply with a blind resume (interactions on Blind Application x Anticipated Discrimination, $p < 0.01$). Following a non-blind rejection, an individual's belief about the extent to which their gender or age contributed to their rejection predicts their future willingness to apply. The larger the role that an individual thinks gender discrimination

[20]The mean Likert scores for the different groups are: 5.0 for women, 4.0 for men, 4.3 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. 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 A7. Among individuals asked to consider non-blind resumes, women and older individuals both perceive a significantly lower likelihood of being hired (by 6.8pp for women compared to men, $p < 0.01$, and by 2.6pp 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.

played in their rejection, the more willing they are to apply again in the future, particularly if their future application is blind. Similarly, the more age discrimination an individual perceived in their rejection, the more willing they are to apply blind in the future.

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 ($p < 0.05$, Appendix Table A12). However, this does not vary by gender or age.[21] 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.[22]

5.2 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 quality 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 0.22 SDs less willing to apply post-rejection ($p < 0.01$, Column 1, Table 3). 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.[23]

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

[22] 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.

[23] Appendix Table A7 presents the results, with the coefficient on post-rejection in Column 1 providing the relevant estimates.

5.2.1 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 3, $p < 0.01$).

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 A7 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 performance sample more after a blind rejection compared to a non-blind rejection (Column 2 versus Column 3).

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 A12 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 (0.59 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 directionally more fair than individuals rejected based on a non-blind resume (by 0.17 points, n.s., Column 3). 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).

5.2.2 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 A13, Column 1). As a result, the gender and age gaps in overall willingness to apply do not increase post-rejection in our setting.

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 3 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), while we estimate no significant difference for men. Older individuals' willingness to apply drops by 50% more after a blind rejection than after a non-blind rejection ($p < 0.01$, column 5), with a more muted difference among younger individuals.

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 A7, 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 A7, 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 A14).

5.2.3 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 4 compares demand for blinding (willingness to apply on blind relative to non-blind 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 4 reveals that, following a non-blind rejection, demand for blinding is significantly greater among women than men (by 0.11 SDs, $p < 0.10$) and older individuals compared to younger individuals (by 0.09 SDs, $p < 0.05$). These patterns are consistent with the idea that following a non-blind rejection, these candidates may 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 4. 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 ($p < 0.10$). 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).

5.2.4 Demand for non-blind versus blind applications: Several explanations

We included several direct questions at the end of our survey on individuals' beliefs and preferences in order to better probe explanations for demand for non-blind versus blind applications.

First, 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 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 5) and older individuals (by 0.3 points, $p < 0.01$). This heterogeneity is consistent with a stronger preference for blinding applications by counter-stereotypical candidates who might anticipate discrimination against their type.

Second, we asked candidates directly about their worries regarding discrimination about gender or age in the 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 (see Appendix Figure A4).[24]. We can relate their answers to their demand for blind applications in our experimental context. Panels A and B of Appendix Figure A5 show that candidates who worry about gender and/or age discrimination in the labor market outside of our experiment have a higher demand for blinding applications within our experimental context, pointing to external relevance of our setting.

We also gave candidates 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 A15). 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 significantly more likely to agree and older individuals significantly less 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

[24]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."

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.

The remaining panels of Appendix Figure A5 show how an individual's endorsement of each of these statements predicts their relative demand for blinding (post-rejection) in our experiment. As expected, participants who expect that revealing their demographics would help them to get an interview have significantly negative demand for blinding (Panel C); similarly, individuals who agree that revealing demographics allows them to share a part of their identity they take pride in have negative demand for blind applications (Panel D). On the other hand, agreement with the fact that revealing demographics can help diversity, equity, and inclusion at the workplace (Panel E) or screen out discriminating employers (Panel F) does not predict demand for blinding in our study. For screening, this may be because individuals do not directly interact with employers in our study. Finally, we find that candidates' concerns that revealing demographic characteristics may create a competence-signaling problem do not predict demand for blinding in our study (Panel G).

5.3 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.[25] 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 A16), with similar overall hiring rates across the two treatments.

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 6 predicts a recruiter's willingness to hire a candidate (in probability points) from the different resume characteristics, with Column (3) presenting results from the non-blind treatment and Column (4)

[25]Panel C of Appendix Table A3 presents summary statistics of recruiter WTH.

presenting results from the blind treatment. Candidates' sample performance on the test strongly predicts 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 3) and in the blind evaluations (Column 4). 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, by approximately 2 percentage points (Column 3 of Table 6, $p < 0.05$). While the overall effect is modest (estimated at 0.06 SDs of WTH), gender discrimination is more pronounced for candidates with better performance signals. Appendix Table A17 presents the results separately for each sample performance. Among candidates with a perfect 2 out of 2 sample performance, 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 1.5 percentage points (or 0.05 SDs) less likely to hire older candidates compared to younger candidates (Column 3 of Table 6, $p \approx 0.12$). This effect appears to be similar across different performance signals (see Columns 2, 3, and 4 of Appendix Table A17).[26][27]

One question we can address with our data is how efficiently recruiters use resume characteristics. That is, are they over-valuing (or under-valuing) certain resume characteristics? Do they rely too much (or too little) on gender or age in the non-blind treatment? To get at this question, Columns (1) and (2) of Table 6 uses our candidate data to illustrate how a risk neutral recruiter looking should weight the different resume characteristics to maximize expected earnings. By us-

[26]Appendix Figure A6 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 A17, counter-stereotypical candidates with stronger signals of performance face more discrimination. We can also explore in-group preferences among recruiters, asking whether the extent of gender (age) discrimination varies by recruiter gender (age). Appendix Table A18 presents the results. We observe that, directionally, male recruiters penalize female candidates more than female recruiters, and younger recruiters penalize older candidates more than older recruiters. However, these differences are modest and not statistically significant. See Appendix Figure A7 for results on in-group preferences broken down by younger men, younger women, older men, and older women.

[27]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 A19). Both male and female recruiters have 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.

ing our candidate data on how different resume characteristics predict full technical test scores (the payoff-relevant object for recruiters), we can analyze the true expected return to each resume characteristic. The results suggest that, across both treatments, recruiters are over-valuing greater education attainment and a stated preference for STEM. While the returns to these characteristics are positive, recruiters over-estimate how informative they are for true test scores. On the other hand, recruiters are actually under-using gender and age relative to its true predictive power. Overall, our recruiter data suggests greater stereotyping on education and STEM-preference than on gender and age.

Our data can also 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, $p < 0.01$), and that younger candidates benefit more from non-blind resumes than older candidates (3.6 v. 2.2, $p < 0.01$).

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, 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.

5.4 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 and (ii) increasing the rate at which 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 approximately top 10% of candidates are hired), a slack market (in which the approximately top 80% of candidates are hired), and a market in between (in which the approximately top 40% of candidates are hired).[28]

We use our data to simulate the pool of hired candidates under blind and non-blind hiring processes for different levels of market tightness.[29] 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 7 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 weakly dominates the non-blind hiring process in terms of our outcomes

[28]We choose these cutoffs as they correspond to different technical test thresholds. For instance, the approximately top 10% of workers corresponds to workers with technical test scores greater than or equal to 7, the approximately top 40% corresponds to technical test scores greater than or equal to 5, and the approximately 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.

[29]To select the pool of hired candidates under a blind (non-blind) process, pre-rejection, 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. The post-rejection estimates in Columns V and VI follow the same process but use candidates' post-rejection application decisions, where blind and non-blind refers to the post-rejection application type.

of interest. The blind hiring process delivers candidates with weakly higher average productivity and weakly increases the share of women and older candidates hired. We estimate that differences in representation across the blind and non-blind treatments weakly increase post-rejection in the tight market. As the labor market grows slacker, this pattern holds, though estimated 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.[30]

6 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 in the application process, in

[30]Another way of considering the efficiency of blind and non-blind processes is to consider how candidates are sorted across the two processes. From the candidate perspective, we can correlate candidate quality (as proxied by technical test score) with likelihood of being hired according to recruiter decisions. This correlation is 0.69 under both blind and non-blind recruiter review. Similarly, recruiters earn on average \$1.35 in expectation per resume reviewed in the blind treatment compared to \$1.33 in the non-blind treatment.

our case eliminating the possibility of discrimination, can have meaningful impacts on the supply-side of the market. Our candidates' responsiveness to anticipated discrimination is echoed in occupation-specific studies in the field, including individuals' choices to mask their ethnicity in a goods market (Zussman, 2013) or clinicians' choices to mask their gender on their websites in more counter-stereotypical medical fields (He et al., 2024). Our findings are also aligned 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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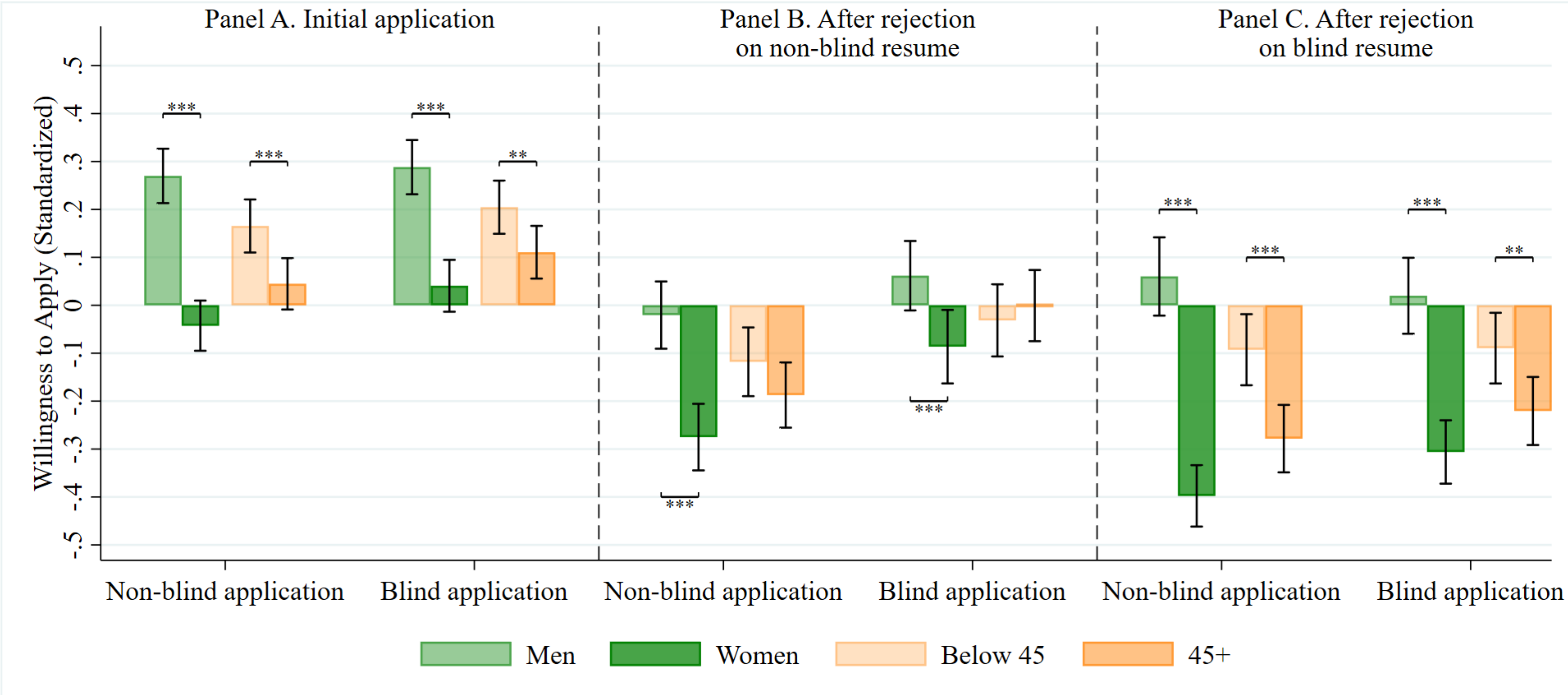
Figures

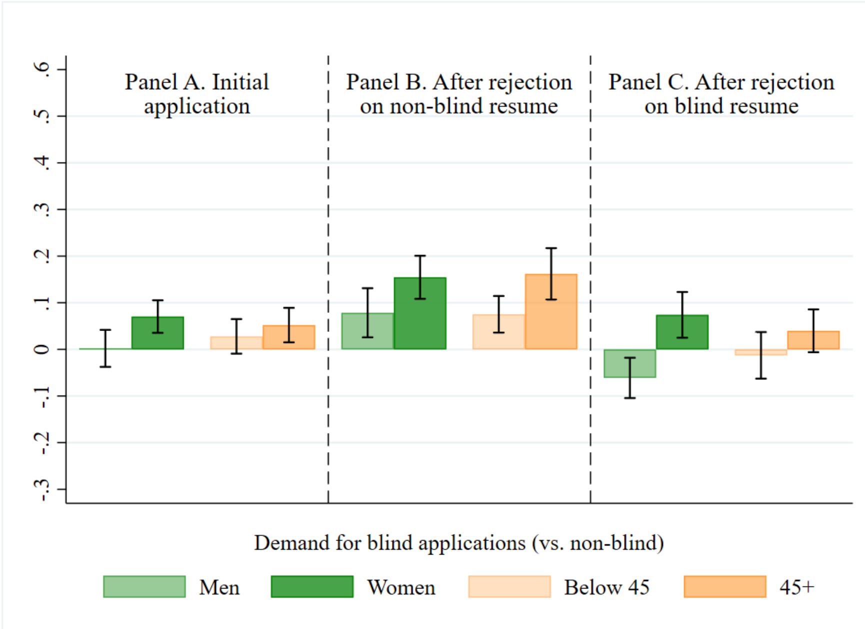
Figure 1. Average Willingness to Apply, by Gender and Age



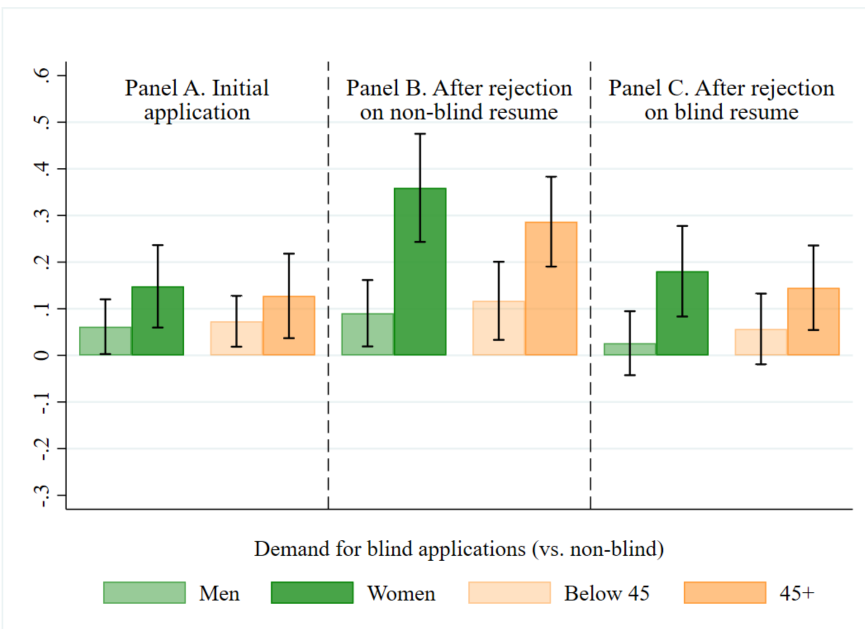
*Notes: Averages are calculated on standardized values. We standardize over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. Panel A includes all applications before rejection feedback ($N = 4,976$). Panel B includes application decisions 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. More Talented Candidates Have Greater Demand for Blind Processes

(a) Test score between 0 and 5



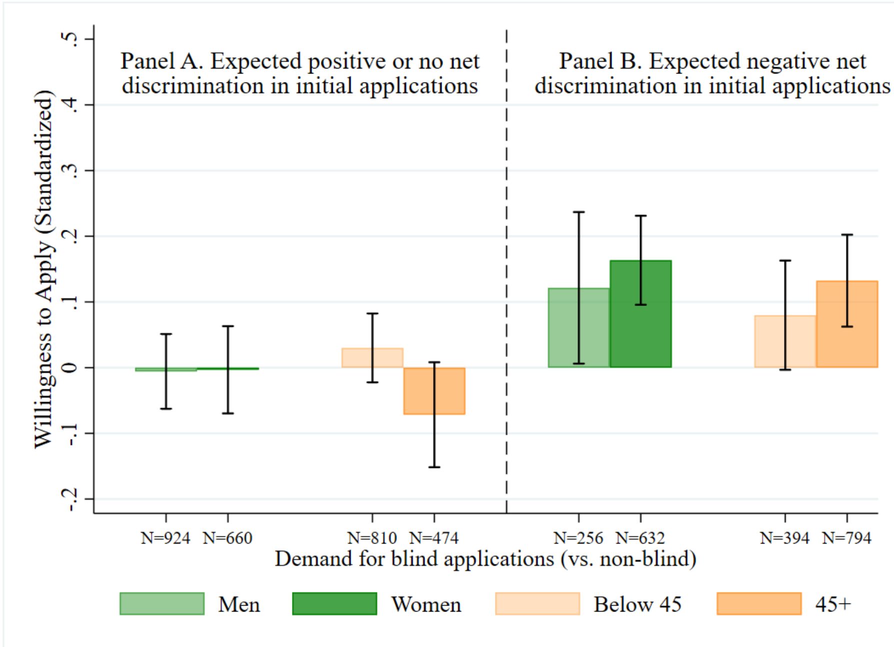
(b) Test score between 6 and 10



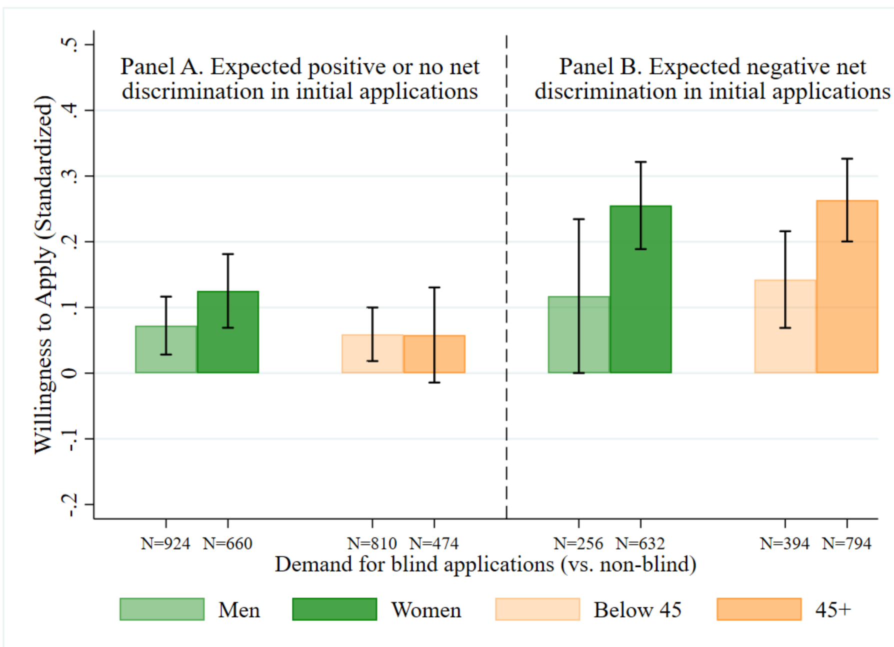
Notes: The figure graphs the average demand for blind applications. Demand for blind application is the difference in standardized willingness to apply under a blind process and standardized willingness to apply under a non-blind process, with positive values indicating greater demand for blind applications. 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

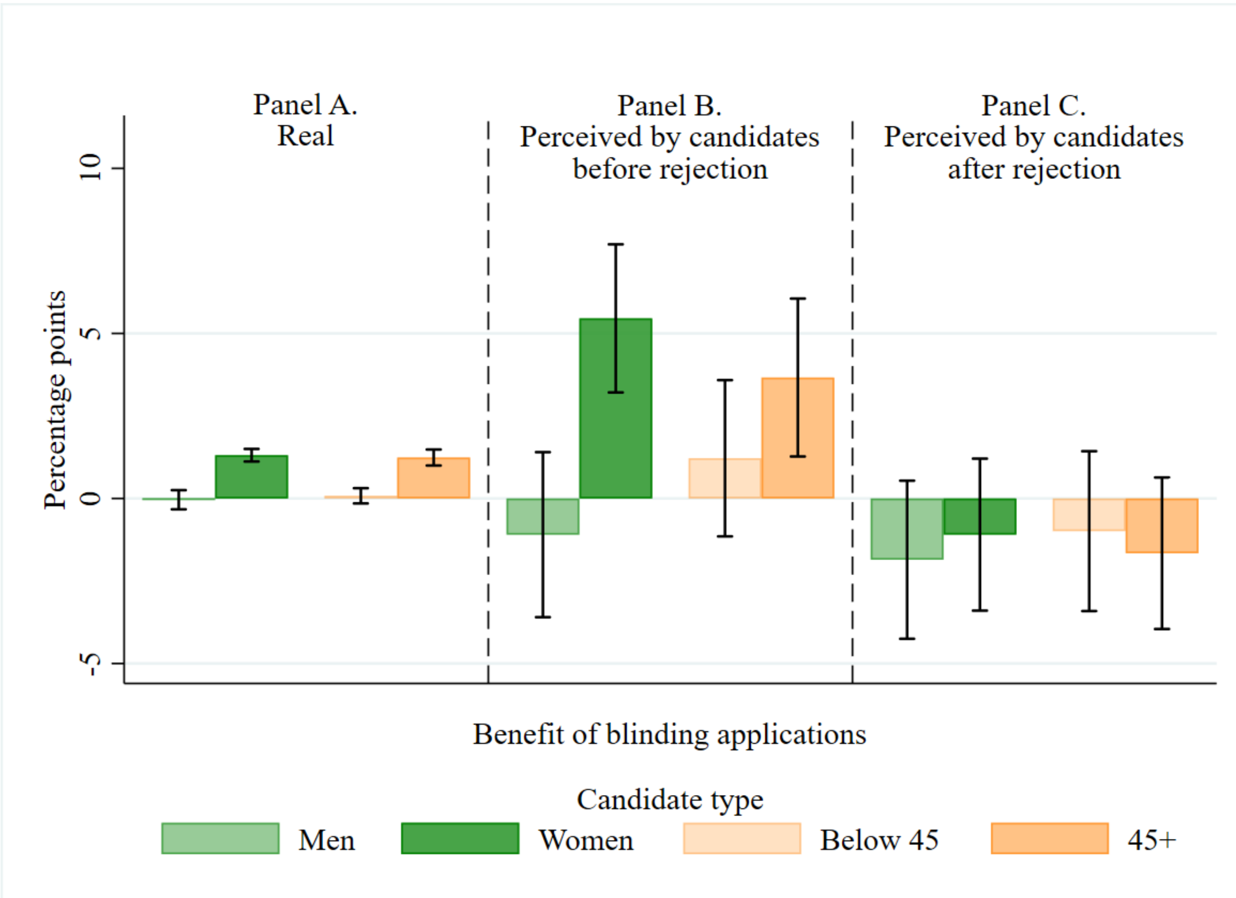


(b) After rejection



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	-0.21***	-0.28***	-0.18***	-0.40***
	(0.04)	(0.04)	(0.05)	(0.05)
Age 45+	-0.09**	-0.11***	-0.07	-0.16***
	(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	0.09	0.09	0.11

*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. OLS Predicting Willingness to Apply Related to Discrimination Beliefs

Dependent variable:	Willingness to apply (standardized)	
	(1)	(2)
Women	-0.214***	-0.181***
	(0.056)	(0.052)
Age 45+	-0.052	-0.054
	(0.059)	(0.055)
Blind application	0.017	-0.033
	(0.017)	(0.022)
Anticipated discrimination: Gender	0.003	
	(0.002)	
Blind application × Anticipated discrimination: Gender	0.004***	
	(0.001)	
Anticipated discrimination: Age	-0.000	
	(0.002)	
Blind application × Anticipated discrimination: Age	0.003***	
	(0.001)	
Beliefs rejection: Gender		0.006**
		(0.002)
Blind application × Beliefs rejection: Gender		0.007***
		(0.002)
Beliefs rejection: Age		0.001
		(0.002)
Blind application × Beliefs rejection: Age		0.005***
		(0.001)
Controls		
Test score	X	X
Favorite subject	X	X
Education	X	X
Observations	2,472	2,472
R^2	0.092	0.109

*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 anticipated 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 (Column 1). After receiving negative feedback on their applications, we ask candidates the following question: "How much do you think the different resume components influenced the recruiter's decision NOT to hire you?" We use the points that candidates provide to gender and age to define their rejection beliefs about gender and age discrimination (Column 2). This table shows coefficient estimates from OLS regressions, where the dependent variable is standardized candidate willingness to apply. 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 3. 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	0.01	0.01	-0.00	0.05	-0.03
	(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	0.10	0.10	0.08	0.10	0.11

*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 4. Demand for Blind Applications, By Rejection Type

Dependent variable:	Difference in (standardized) Willingness to apply Blind − Non-blind		
	All	Non-blind rejection	Blind rejection
	(1)	(2)	(3)
Women	0.08***	0.06*	0.08**
	(0.02)	(0.04)	(0.03)
Age 45+	0.03	0.00	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 5. Predictors of Candidates' Preferences for Blind Applications

Dependent variable:	Stated preference for blind applications						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Women	0.65***	0.18***	0.81***	0.77***	0.72***	0.62***	0.30***
	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
Age 45+	0.32***	-0.07	0.24***	0.29***	0.29***	0.33***	-0.01
	(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***				-0.01
			(0.03)				(0.03)
Screening				-0.42***			-0.12***
				(0.03)			(0.03)
Identity					-0.59***		-0.23***
					(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	0.43	0.16	0.15	0.23	0.08	0.48

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.*

Table 6. Returns to Resume Characteristics

Dependent variable:	Probability of Being Hired			
	Optimal Risk-Neutral Decisions		Observed Decisions	
	Non-Blind	Blind	Non-Blind	Blind
Women	-0.030***		-0.020**	
	(0.0067)		(0.0093)	
45+	-0.028***		-0.015	
	(0.0065)		(0.0096)	
Bachelor's Degree	0.031***	0.030***	0.076***	0.086***
	(0.0073)	(0.0074)	(0.011)	(0.011)
Advanced Degree	0.059***	0.054***	0.10***	0.12***
	(0.0091)	(0.0092)	(0.012)	(0.012)
Social Sciences	-0.013	-0.0066	-0.0019	0.013
	(0.0082)	(0.0082)	(0.010)	(0.010)
STEM	0.035***	0.046***	0.13***	0.15***
	(0.0084)	(0.0082)	(0.013)	(0.012)
Resume score: 1	0.13***	0.13***	0.15***	0.15***
	(0.0088)	(0.0089)	(0.012)	(0.011)
Resume score: 2	0.16***	0.16***	0.33***	0.34***
	(0.0093)	(0.0093)	(0.014)	(0.014)
Constant	0.20***	0.17***	0.067***	0.032***
	(0.011)	(0.0098)	(0.014)	(0.011)
Observations (Clusters)	2488	2488	2812 (597)	2889 (620)
Adjusted R-squared	0.162	0.150	0.257	0.283

*Notes: This table shows coefficient estimates from OLS regressions, where the dependent variable is likelihood of being hired in probability. Columns (1) and (2) show how a risk neutral recruiter would value the resume characteristics if they were maximizing expected earnings. We predict technical test scores from resume characteristics using the observed candidate data and use this mapping to compute the true expected return to the resume characteristics. Columns (3) and (4) show how recruiters in the Recruiter Study actually weight resume characteristics using their observed hiring decisions. Columns (3) and (4) cluster standard errors at the recruiter level. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

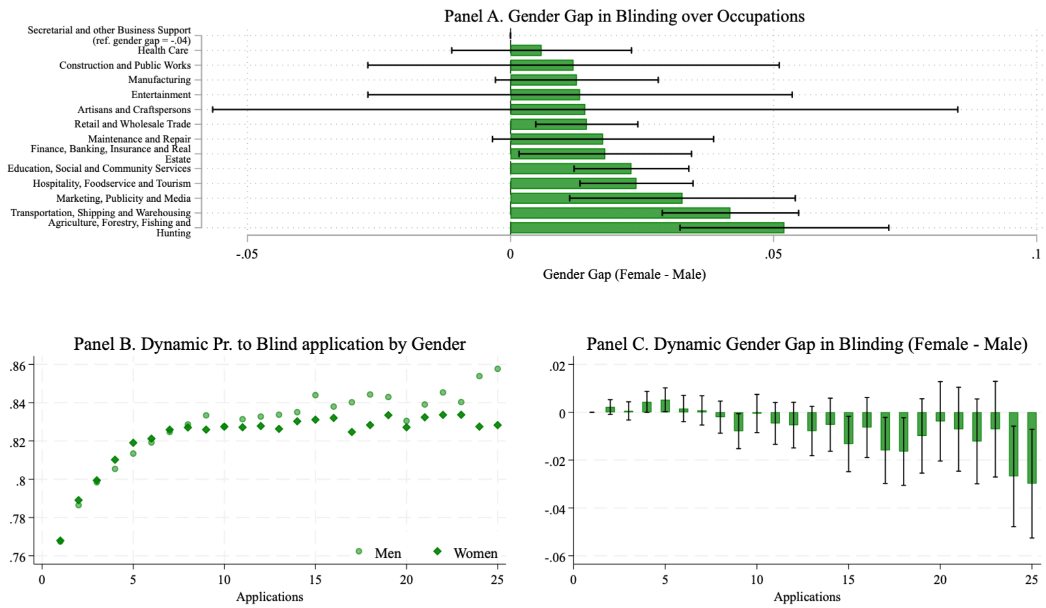
Table 7. Comparing Outcomes under Blind and Non-Blind Hiring Processes

	Top Scores	Random	Blind Pre-Rej.	Non-Blind Pre-Rej.	Blind Post-Rej.	Non-Blind Post-Rej.
Panel A: Tight Market (# of Positions = 292)						
Average Score	7.79	4.12	6.22	6.07	6.07	6.02
Share Women	35%	53%	36%	33%	37%	30%
Share > 45	43%	52%	47%	45%	49%	46%
Panel B: Intermediate Market (# of Positions = 917)						
Average Score	6.16	4.12	5.05	5.04	4.99	4.95
Share Women	45%	53%	44%	41%	44%	40%
Share > 45	45%	52%	50%	48%	51%	49%
Panel C: Slack Market (# of Positions = 1991)						
Average Score	4.73	4.12	4.29	4.28	4.34	4.35
Share Women	52%	53%	51%	51%	49%	48%
Share > 45	51%	52%	50%	50%	50%	49%

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 292 candidates are hired; the middle panel simulates outcomes when 917 candidates are hired; the bottom panel simulates outcomes when 1,991 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 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. Columns III and IV use candidates' pre-rejection decisions; Columns V and VI use candidates' post-rejection application decisions.

A Additional Figures and Tables

Figure A1. Gender Gaps in blinding propensity in the labor market



Notes: Panel A: Displays heterogeneity estimates of the within-job offer gender gap (female − male) in masking one's name over broad occupation categories used by the French PES (14 level-1 codes). Panel B: Within-candidate evolution of name blinding over time-stamped applications by gender. Panel C: point estimates and confidence intervals of the gender gap (female − male) corresponding to the dynamic means in B. Reference category is the applicant's first observed telecandidature. $N = 1,282,145$ *application-vacancy pairs. Source SISP, October to April for 2014–2015. Standard errors clustered at the candidate level.*

Figure A2. Distribution of Candidate Test Scores, by Gender and Age

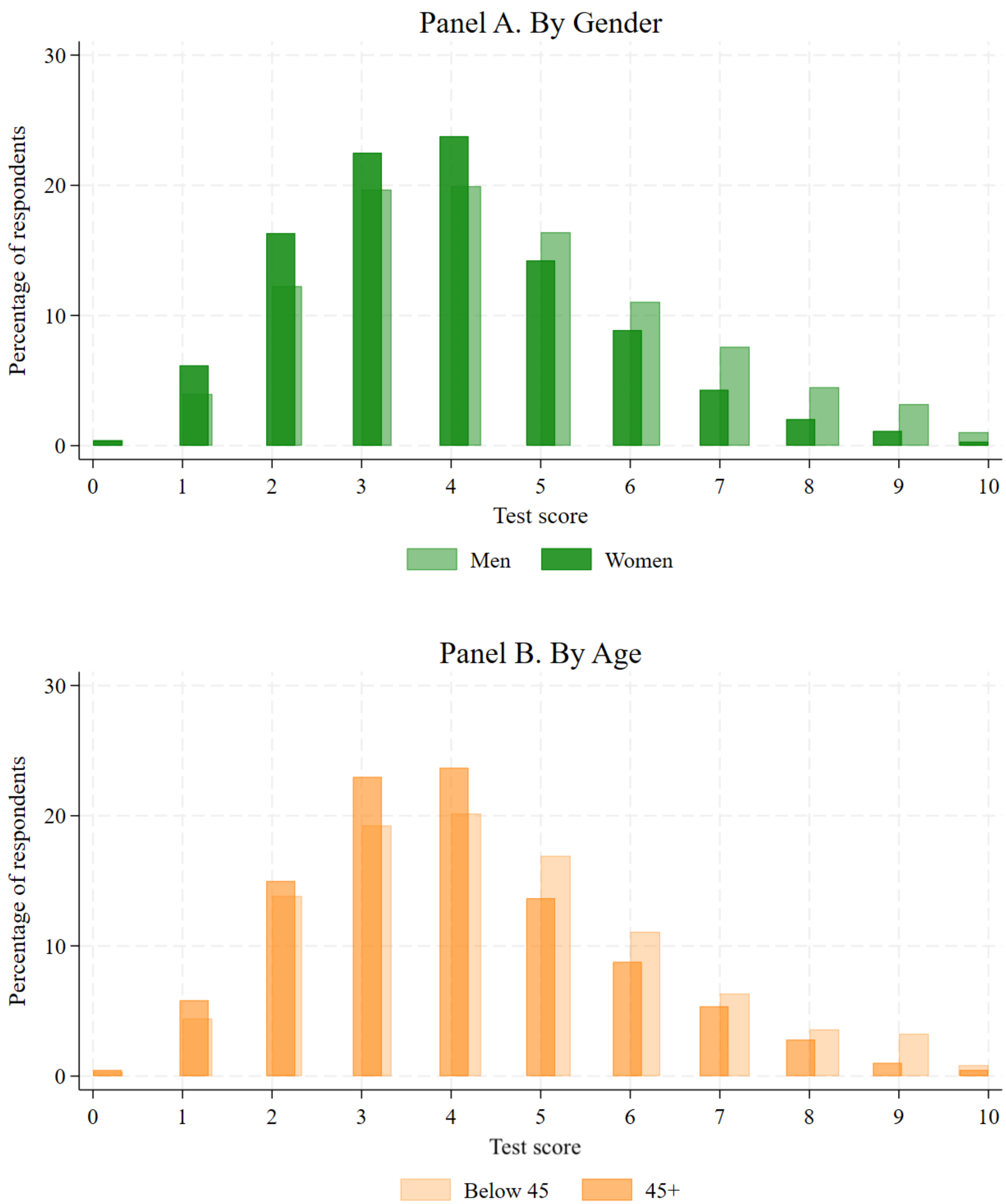
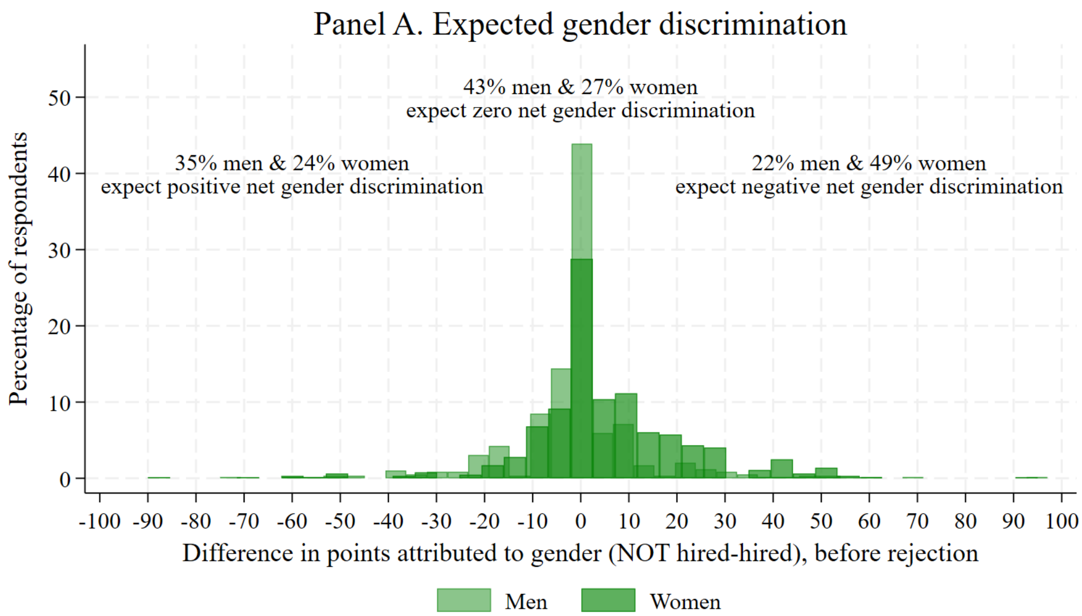
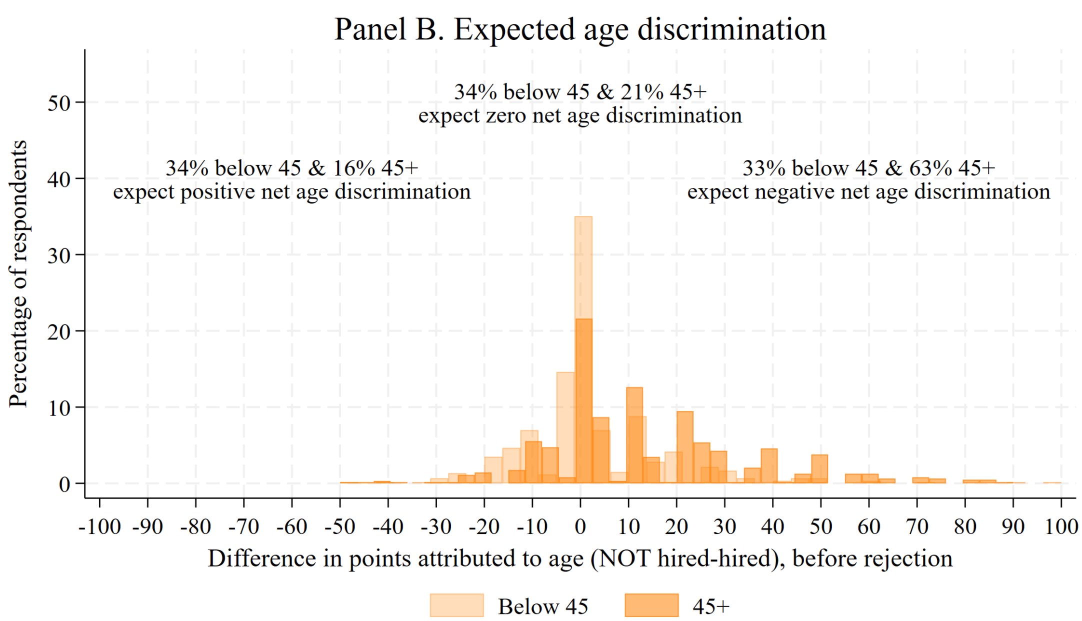


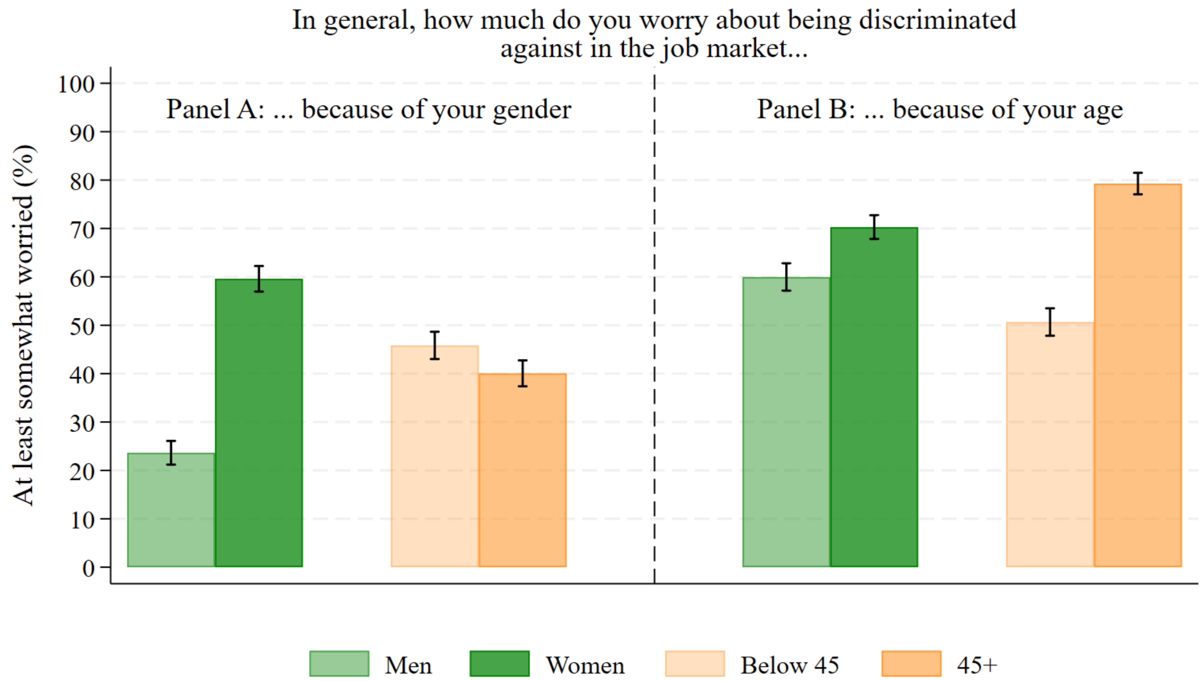
Figure A3. Candidates' Expected Gender and Age Discrimination Before Rejection





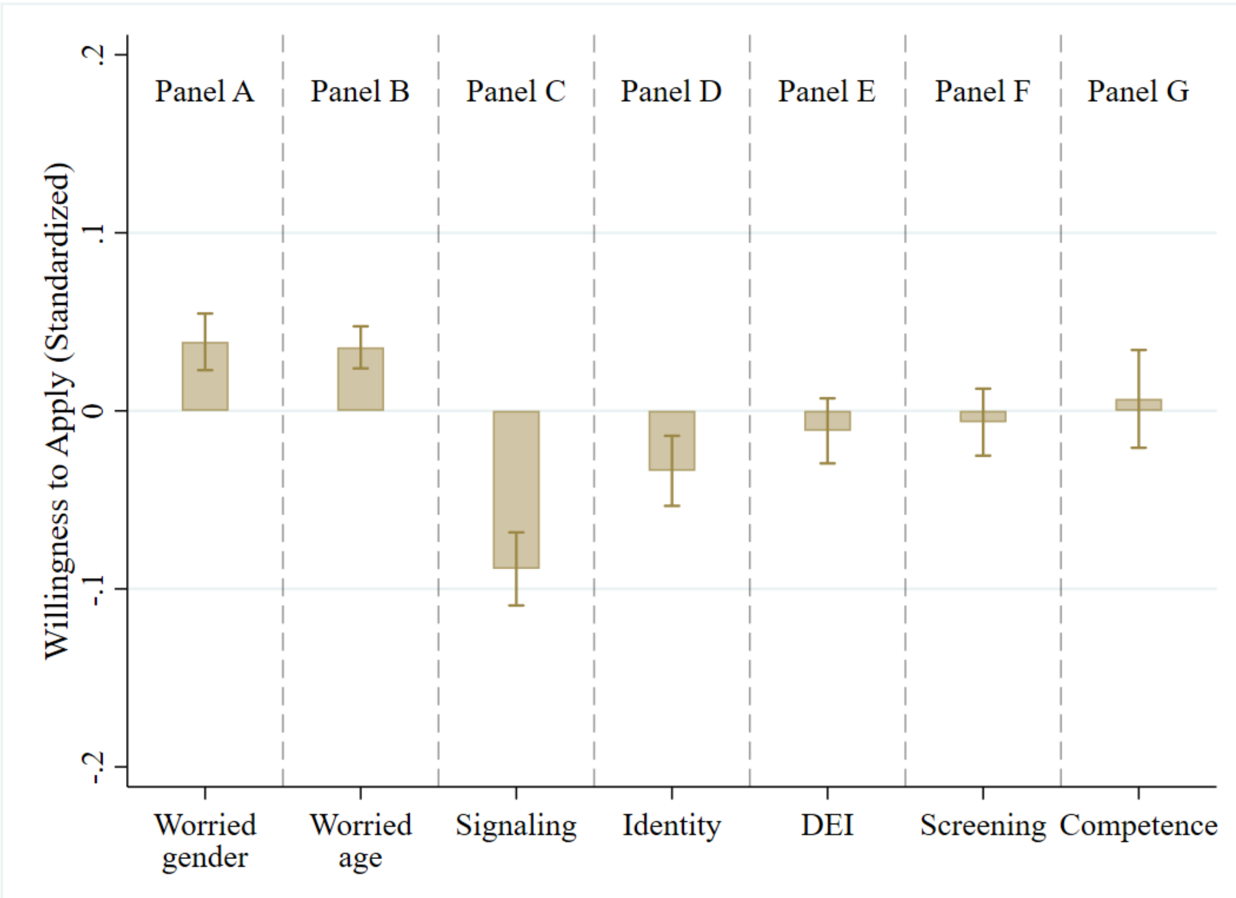
Notes: After they completed the initial two price lists, we asked the following question to candidates, based on the randomly selected resume: "Imagine that a recruiter saw this resume and decided to hire you. How much do you think the different resume components influenced the recruiter's decision? 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 A4. Candidates' Perception of Discrimination in the Broader Labor Market



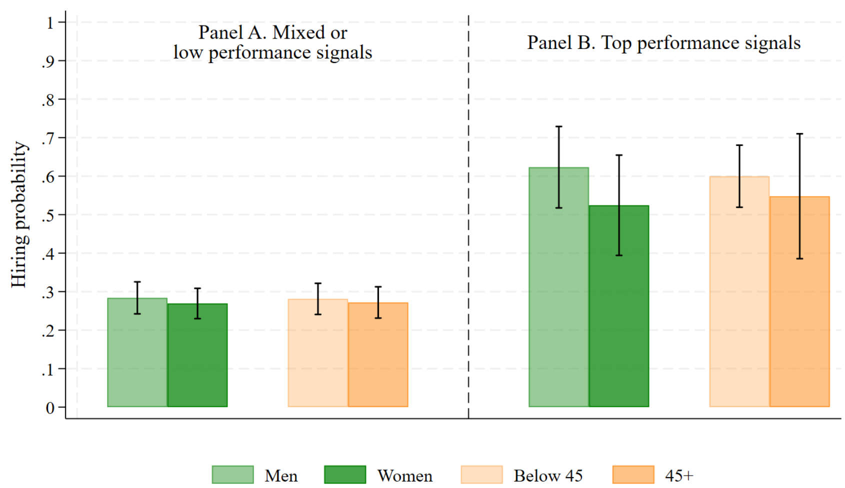
Notes: At the end of the survey, we asked candidates about their experiences of discrimination and their preferences regarding blind application processes in the labor market. This figure shows the share of respondents who answered that they were at least somewhat worried "about being discriminated against 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).

Figure A5. Candidates' Willingness to Apply Blind vs. Non-Blind: Mechanisms



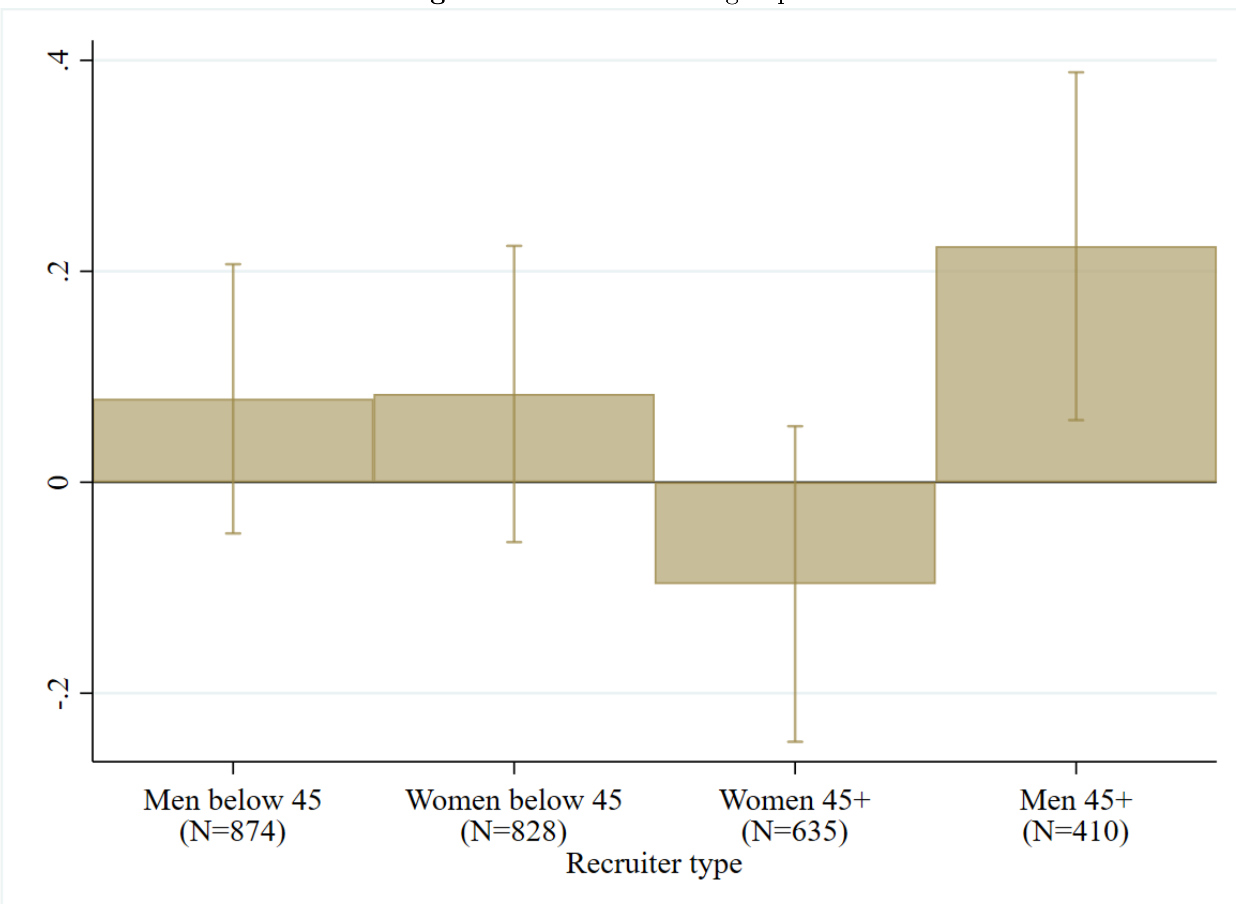
Note: Bars display coefficient estimates from seven separate OLS regressions in which the dependent variable is standardized candidate willingness to apply. The figure reports the coefficients on the interaction between Blind Applications (after rejection) and each variable shown. The variables are based on survey questions asked at the end of the study about candidates' experiences with discrimination and their preferences regarding blind application processes in the labor market. Specifically, following negative feedback, the figure shows interaction coefficients between Blind Applications and: candidates' concerns about discrimination in the job market due to gender (Panel A) or age (Panel B); beliefs about whether their demographic characteristics help them obtain an interview (Signaling, Panel C); preferences for revealing aspects of their identity they are proud of (Identity, Panel D); beliefs that revealing demographic characteristics supports diversity, equity, and inclusion (DEI, Panel E); beliefs that revealing such characteristics helps screen out discriminating employers (Screening, Panel F); and concerns that revealing demographic characteristics may create doubt about whether selection is based on competence rather than identity (Panel G). The exact wording is detailed in Table 5 and Appendix F. All regressions include fixed effects for test scores, favorite subject, and level of education. Whiskers mark 95% confidence intervals.

Figure A6. Recruiters' Hiring Probabilities, Non-Blind Applications



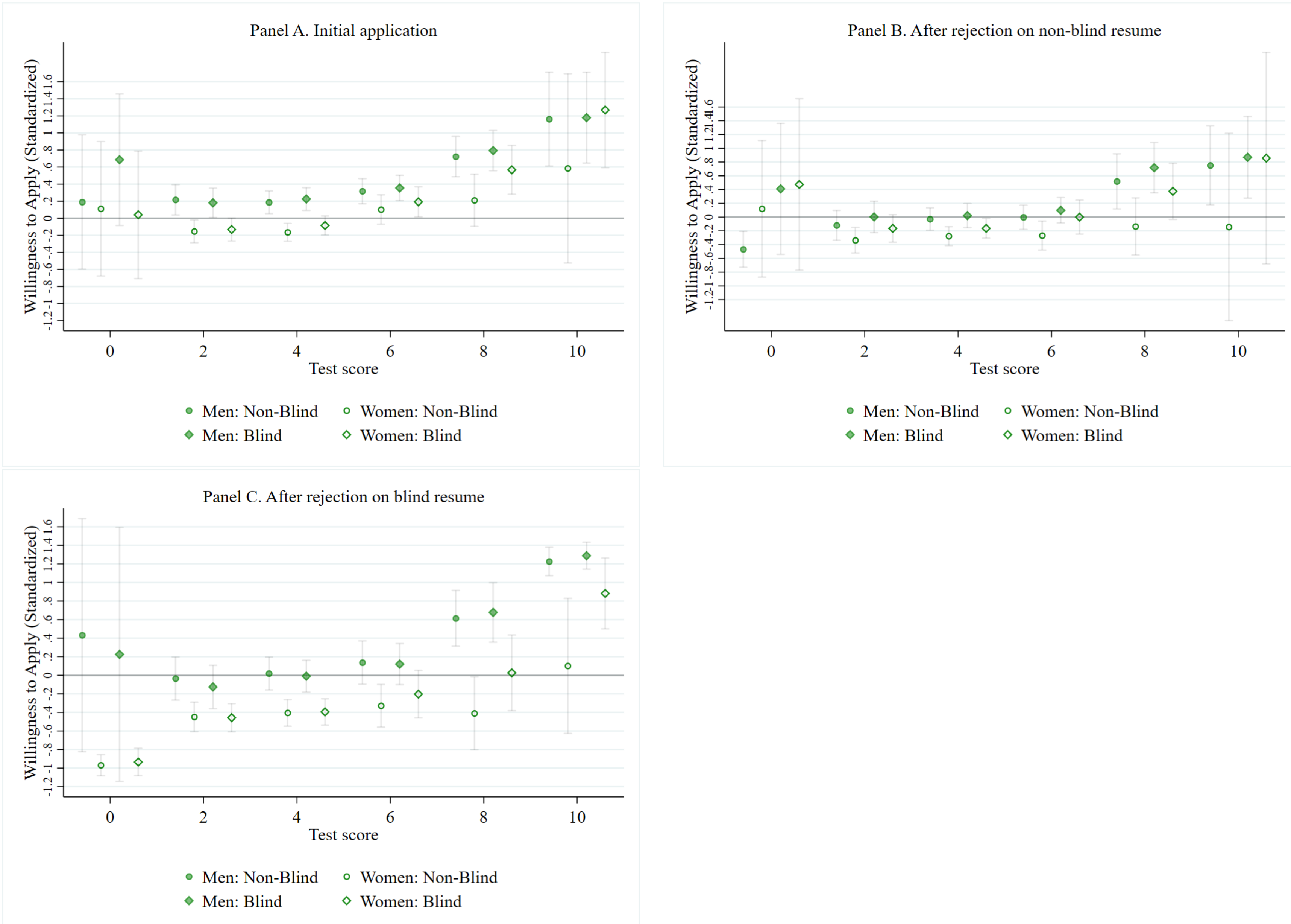
Notes: Bars represent recruiters' mean probabilities of hiring candidates in the non-blind resume treatment, by candidate gender and age. Panel B shows hiring probabilities for resumes with top performance signals, that is, STEM and a sample test score of 2 out 2. Panel A shows the mean probabilities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

Figure A7. Recruiters' in-group bias



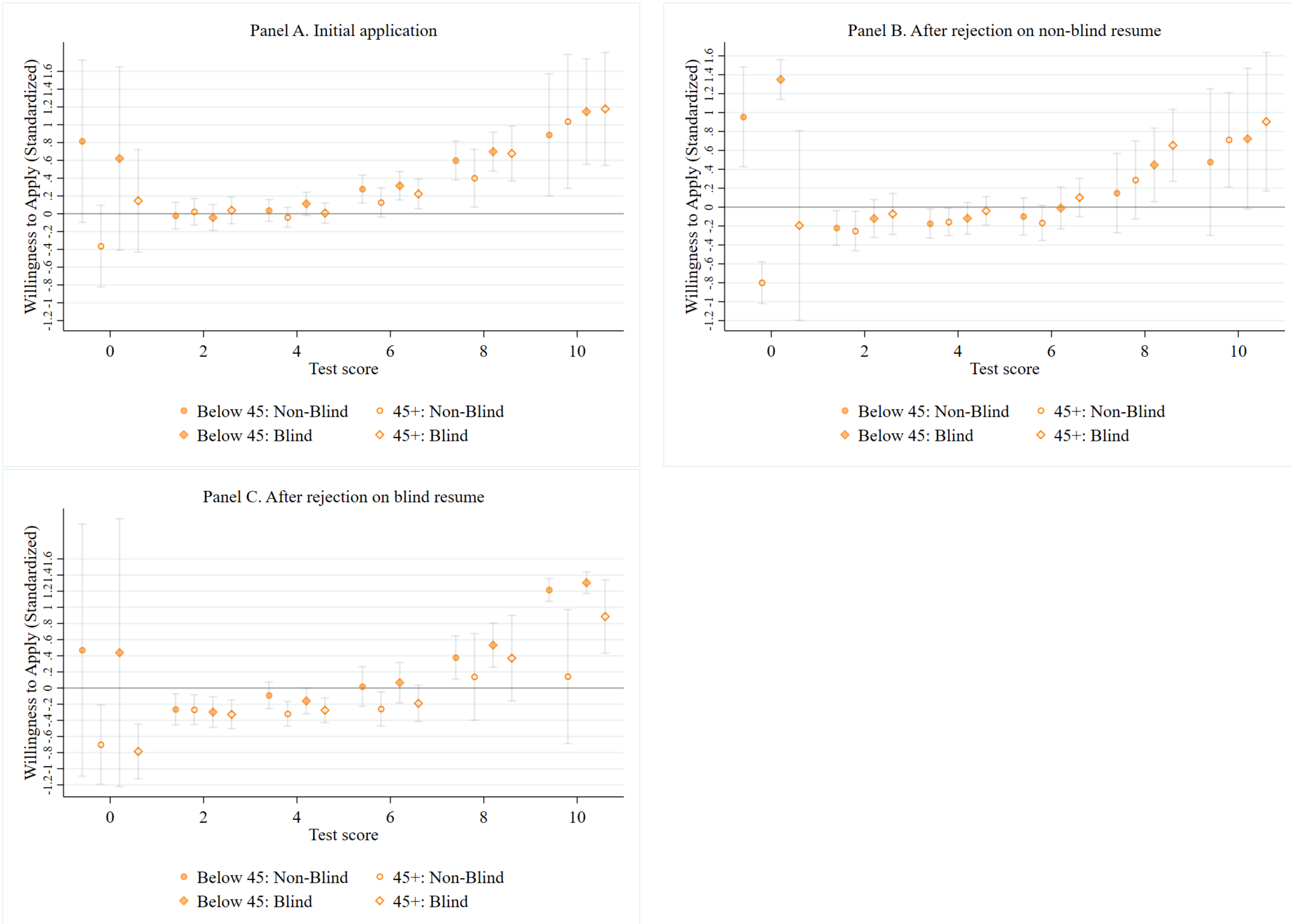
Notes: Bars represent the premium in terms of standardized willingness to hire that recruiters provide to candidates of the same type (in the non-blind regime). Regressions include fixed effects for candidates' resume characteristics: education, favorite subject, and sample performance. The number of observations are in parentheses.

Figure A8. Relationship Between Candidates' Willingness to Apply and Test Score, by Gender



Notes: The figure graphs the average standardized willingness to apply, at different test scores, for men and women, with either the blind or the non-blind application. 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 shows results on the pre-rejection decisions. Panel B shows application decisions following a rejection with a non-blind resume. Panel C shows application decisions following a rejection with a blind resume. Whiskers mark 95% confidence intervals.

Figure A9. Relationship Between Candidates' Willingness to Apply and Test Score, by Age



Notes: The figure graphs the average standardized willingness to apply, at different test scores, for young and older candidates, with either the blind or the non-blind application. 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 shows results on the pre-rejection decisions. Panel B shows application decisions following a rejection with a non-blind resume. Panel C shows application decisions following a rejection with a blind resume. Whiskers mark 95% confidence intervals.

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	4.12	4.44	3.85	0.00	4.32	3.94	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	4.15	4.10	0.56
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	4.23	4.02	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. 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	-0.00	-0.02	0.02	-0.06**
	(0.02)	(0.02)	(0.03)	(0.03)
Women below 45	-0.21***	-0.27***	-0.12	-0.44***
	(0.06)	(0.05)	(0.07)	(0.08)
Men 45+	-0.09	-0.10*	-0.01	-0.20**
	(0.06)	(0.05)	(0.07)	(0.08)
Women 45+	-0.30***	-0.40***	-0.25***	-0.56***
	(0.06)	(0.05)	(0.07)	(0.08)
Blind application × Women below 45	0.08***	0.12***	0.13***	0.12***
	(0.03)	(0.03)	(0.04)	(0.04)
Blind application × Men 45+	0.04	0.08***	0.13***	0.04
	(0.03)	(0.03)	(0.04)	(0.04)
Blind application × Women 45+	0.09***	0.19***	0.20***	0.18***
	(0.03)	(0.03)	(0.04)	(0.04)
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-squared	0.08	0.09	0.09	0.11

*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 A5. Willingness to Apply 1st Price List

Dependent variable:	WTA (standardized)
Blind application	-0.03
	(0.07)
Women	-0.20***
	(0.06)
Age	-0.06
	(0.06)
Blind × Women	0.03
	(0.08)
Blind × Age 45+	-0.04
	(0.08)
Controls	
Test score	X
Favorite subject	X
Education	X
Observations	2,488
R^2	0.09

*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. Regression includes 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 A6. OLS Predicting Beliefs about Test Performance

Dependent variable:	Believed score
	(1)
Women	-0.56***
	(0.09)
Age 45+	-0.06
	(0.09)
Controls	
Test score	X
Favorite subject	X
Education	X
Observations	2,488
R^2	0.23

*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 A7. 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	-0.21***	-0.20***	-0.22***	-0.54***	-0.49***	-0.59***	-3.11***	-6.83***	0.50
	(0.03)	(0.04)	(0.04)	(0.06)	(0.09)	(0.09)	(0.88)	(1.24)	(1.25)
Age 45+	0.09***	0.07*	0.11***	0.10	0.15*	0.04	-1.33	-2.56**	0.06
	(0.03)	(0.04)	(0.04)	(0.06)	(0.09)	(0.09)	(0.86)	(1.21)	(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	0.13	0.13	0.13	0.20	0.21	0.20	0.14	0.14	0.17

*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 A8. 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	-0.22***	-0.14***	-0.14***	-0.07
	(0.04)	(0.04)	(0.04)	(0.04)
Age 45+	-0.10**	-0.11***	-0.06	-0.08**
	(0.04)	(0.04)	(0.04)	(0.04)
Believed test score		0.22***		0.22***
		(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	0.08	0.12	0.09	0.12

*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 A9. Pre-Rejection Demand for Blinding by Candidate Quality

	(1)
Dependent variable:	Willingness to apply (standardized)
Blind application	-0.09**
	(0.04)
Women	-0.22***
	(0.04)
Age 45+	-0.10**
	(0.04)
Test score	0.06***
	(0.01)
Blind application × Women	0.08***
	(0.02)
Blind application × Age 45+	0.03
	(0.02)
Blind application × Test score	0.02***
	(0.01)
Controls	
Favorite subject	X
Education	X
Observations	4,976
R^2	0.08

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

Table A10. OLS Predicting Relative Benefit of Blinding

	Benefit of Blinding
	(1)
Women	1.00***
	(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 A11. OLS Predicting Candidates' Beliefs about Discrimination

Dependent variable:	Anticipated Discrimination Initial Applications		Discrimination Beliefs Post-Rejection	
	Gender	Age	Gender	Age
	(1)	(2)	(3)	(4)
Women	8.20***	3.18***	6.33***	0.67
	(0.91)	(1.12)	(0.69)	(0.89)
Age 45+	-1.86**	11.55***	-0.63	10.36***
	(0.87)	(1.05)	(0.66)	(0.86)
Beliefs test score	0.74***	0.54**	0.62***	0.72***
	(0.22)	(0.27)	(0.18)	(0.25)
Test score	0.41	0.39	0.43**	-0.12
	(0.25)	(0.30)	(0.21)	(0.26)
Social Sciences	0.49	-1.56	0.42	-0.24
	(1.10)	(1.36)	(0.80)	(1.07)
STEM	3.37***	0.91	1.74**	1.95*
	(1.10)	(1.35)	(0.86)	(1.08)
Bachelor's	7.47***	3.66***	3.93***	4.10***
	(1.02)	(1.14)	(0.73)	(0.93)
Advanced	7.73***	7.70***	5.35***	5.89***
	(1.15)	(1.49)	(0.94)	(1.18)
Observations	2,472	2,472	2,472	2,472
R^2	0.14	0.13	0.12	0.15

*Notes: . Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table A12. OLS Predicting Feelings of Disappointment and Perceptions of Fairness

Dependent variable:	Disappointment		Fair
	Anticipated	Realized	rejection
	(1)	(2)	(3)
Women	0.04	-0.08	0.25***
	(0.15)	(0.16)	(0.09)
Age 45+	0.23	0.02	-0.12
	(0.15)	(0.16)	(0.09)
Blind application	-0.47**	-0.59***	0.17
	(0.18)	(0.19)	(0.10)
Blind application × Women	-0.09	-0.18	0.11
	(0.21)	(0.22)	(0.12)
Blind application × Age 45+	-0.02	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	0.12
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 A13. 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	-0.19***	-0.19***	-0.21***
	(0.04)	(0.05)	(0.05)
Age 45+	-0.09**	-0.05	-0.13**
	(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	0.10	0.09	0.12

*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 A14. 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	-0.13***	-0.19***	-0.08
	(0.05)	(0.05)	(0.05)
Age 45+	-0.02	-0.07	0.03
	(0.05)	(0.05)	(0.05)
Blind rejection	0.08	0.13**	0.04
	(0.06)	(0.07)	(0.07)
Blind rejection × Women	-0.18**	-0.20***	-0.17**
	(0.07)	(0.07)	(0.08)
Blind rejection × Age 45+	-0.11	-0.09	-0.14*
	(0.07)	(0.07)	(0.07)
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 A15. 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***	0.38***	0.28***	0.13***	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	0.09	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 A16. Impact of Blind Applications on Willingness to Hire

Dependent variable:	Willingness to hire (standardized)				
	(1)	(2)	(3)	(4)	(5)
Blind	0.03	0.03	0.04	0.03	0.04
	(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	5,701	5,701
R^2	0.00	0.27	0.30	0.29	0.31

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 A17. 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. Columns (1) to (4) show results for recruiters randomly assigned to evaluate non-blind applications, and columns (5) to (8) for those randomly assigned to evaluate blind applications. Columns (1) and (5) show pooled results. Columns (2) to (4) and (6) to (8) present regression results by candidate sample test score (0, 1 or 2 out 2). 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 A18. Recruiter Decisions, by Recruiter Gender and Age

Dependent variable:	Willingness to hire (standardized)				
	Recruiter Gender		Recruiter Age		
	Men	Women	Below 45	45+	All
	(1)	(2)	(3)	(4)	(5)
Candidate: Women	-0.09*	-0.03	-0.07*	-0.07	-0.09*
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
Candidate: Age 45+	0.02	-0.12***	-0.06	-0.02	-0.06
	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Recruiter: Women			-0.17**	-0.22**	-0.22***
			(0.07)	(0.09)	(0.07)
Recruiter: Age 45+	-0.23***	-0.16**			-0.20***
	(0.08)	(0.07)			(0.07)
Candidate: Women × Recruiter: Women					0.06
					(0.06)
Candidate: Age 45+ × Recruiter: Age 45+					0.03
					(0.07)
Controls					
Recruiter race/ethnicity	X	X	X	X	X
Recruiter & candidate favorite subject	X	X	X	X	X
Recruiter & candidate education	X	X	X	X	X
Resume score	X	X	X	X	X
Observations	1,284	1,463	1,757	1,055	2,747
R^2	0.28	0.31	0.28	0.32	0.29

*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. All regressions include fixed effects for recruiter race or ethnicity, favorite subject, and level of education, as well as candidate favorite subject, education, and resume score. Regressions include only recruiters who identify as either men or women. Clustered standard errors at the recruiter level are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table A19. 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	4.44	1.06
Women	5.06	3.85	1.21
Below 45	5.57	4.32	1.25
45+	4.57	3.94	0.63
STEM	7.40	4.58	2.82
Social sciences	3.87	3.84	-0.03
Humanities	3.43	3.92	-0.49
Advanced degree	6.62	4.51	2.11
Bachelor's	5.58	4.22	1.36
High school	3.33	3.78	-0.45

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.

B Technical test

Bold answer choices indicate the correct response.

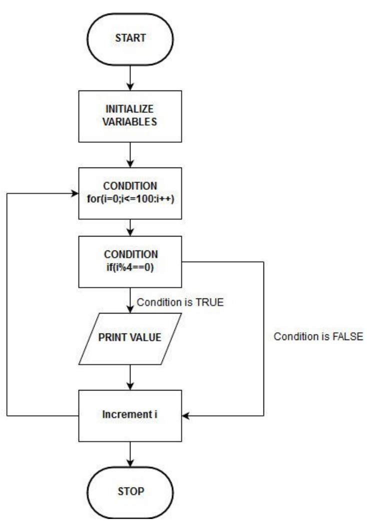
1. Data Set A: flower, cat, dog, house
   Data Set B: cat, bird, flower, door

   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

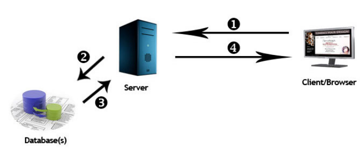
5. You are coding a new video game and have run into an issue. You want to create a main menu that allows the player to press 1 to play with only one player, to press 2 for multiplayer, or to press Q to quit the game. You would like all players to see this menu at least once at the beginning of the game. 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. Instructions for Recruiters: Non-Blind Resume Treatment

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 Recruiters Could be 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 Blind Resume that Recruiters Could be 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 do not pay enough attention to instructions and who provide 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 do 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 answer all ten test questions correctly). A recruiter who understands 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 the 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.[31] We restrict our final sample to those respondents measured to have a maximum reading speed of 400 words per minute on the main instructions pages that describe the multiple price lists.[32]

Table E1 presents the percentage of respondents in both surveys who fail each test. Some respondents fail more than one test.

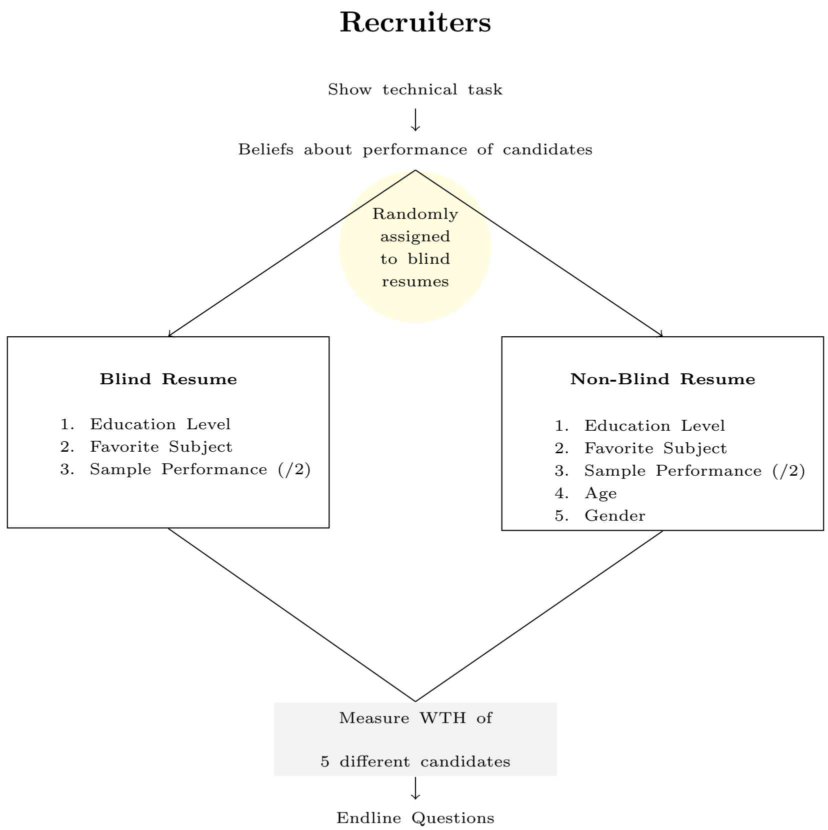
Table E1. Percentage of respondents who fail the different checks

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*

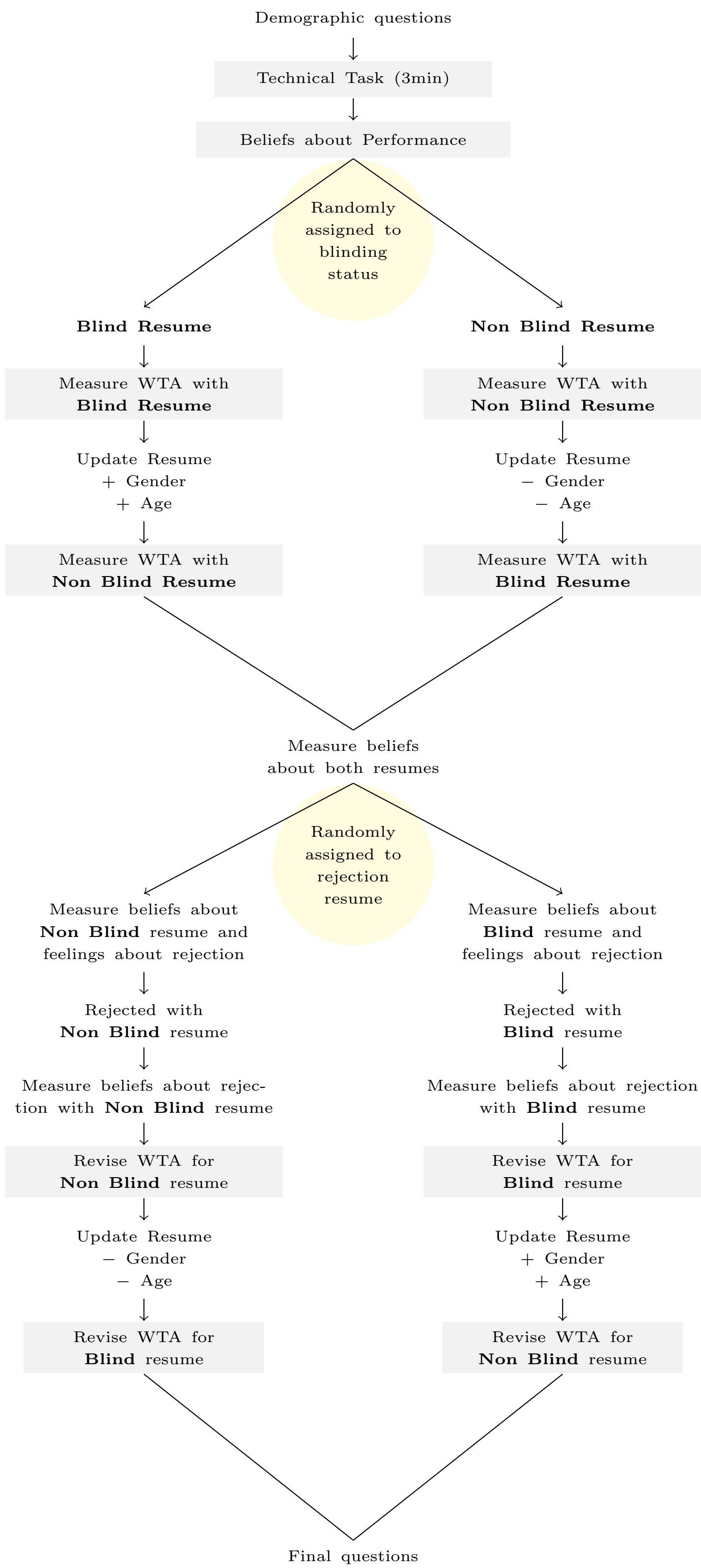
[31] https://www.qualtrics.com/support/survey-platform/survey-module/survey-checker/survey-methodology-compliance-best-practices/.

[32] 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

F.1 Recruiter Survey

What is the purpose of this research?

In this academic study, we are interested in understanding the dynamics of job search. You will be serving as a recruiter in this study. Our goal is to understand your willingness to hire a variety of different potential job candidates.

What can I expect if I take part in this research?

You will complete an online survey. It should take you no more than 15 minutes.

You will have no direct interaction with any other participant, but the decisions you make may impact the earnings of other participants in a different part of the study. In addition, your responses in this study will be anonymized and may be used in another study where other participants will view them. These participants will not receive identifying information about you, and you will not receive identifying information about them. You will be told how your decisions may impact the earnings of other participants.

You will earn $3 for completing the study. This payment will be made to you through the Prolific platform within 48 hours of your participation.

In addition, 10% (1 out of 10) participants will be randomly selected for bonus payment opportunities. If you are randomly selected to earn incentive pay, you may earn between $0-$10.50 based upon your decisions in this study. We expect average additional pay to be approximately $5.50 for those randomly selected for incentive pay. This additional payment will be made through Prolific within two weeks of your participation.

Your answers will be linked to your Prolific ID at the time of the study. However, we will delete your Prolific ID from the stored dataset after completing study payments. Only data without your Prolific ID will be analyzed or shared. No other identifying information will be collected.

This survey contains understanding and attention questions. If you answer an understanding question incorrectly, or if you fail to answer an attention question within the given time frame, you may be dismissed from the study and may not receive payment. For that reason, you should read the instructions carefully and should not navigate away from the survey page during your participation.

What should I know about a research study?

- Whether or not you take part is up to you.
- Your participation is completely voluntary.
- You can choose not to take part.
- You can agree to take part and later change your mind.
- Your decision will not be held against you.
- Your refusal to participate will not result in any consequences or any loss of benefits that you are otherwise entitled to receive.
- You can ask all the questions you want before you decide.

You may not be told everything

As part of this research design, you may not be told everything about the purpose of this study. In addition, while you will have complete and truthful information about the procedures of the version of the study that you are participating in, there may be other versions of the study with different procedures. You will not be told about these other versions.

Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at Katherine Coffman, Harvard Business School, 617 495 6538 or kcoffman@hbs.edu.

Incentives

In this study, we're exploring job search dynamics. You'll act as a recruiter for a job opportunity. Our aim is to know how willing you are to hire different job candidates.

You'll receive a guaranteed $3 for finishing the study.

Additionally, every participant who completes the study will have a 10% chance of being randomly chosen to earn extra payment based on their decisions.

More information about the additional payment is provided in the following instructions. If you are not selected, you'll only receive the guaranteed $3.

Overview

Thank you for your participation today! In this study, you will evaluate five resumes of real candidates from Prolific. For each resume, you will decide how willing you would be to link your bonus payment to that candidate's performance on a **technical test**.

The Technical Test

Before we show you any resumes, let's introduce the test candidates take. It is a 10-question multiple-choice test assessing technical skills like coding and programming.

Below are the 10 questions. Candidates saw these questions in random order. The test had a time limit and used images to prevent online searching or copying.

Please review the test now. No need to answer the questions.

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

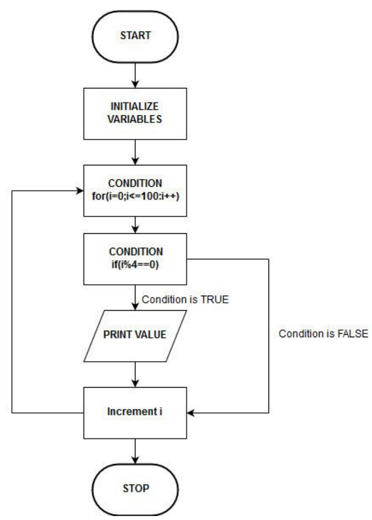
D. cat, flower

```
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:
   What is its output?

   A. The value of z is x + y.
   B. **The value of z is 11.**

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

C. x + y

D. 11

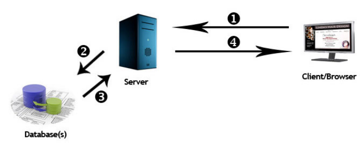
5. You are coding a new video game and have run into an issue. You want to create a main menu that allows the player to press 1 to play with only one player, to press 2 for multiplayer, or to press Q to quit the game. You would like all players to see this menu at least once at the beginning of the game.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

Performance of Candidates

We are curious how you believe candidates from Prolific performed on this technical test. Specifically, think about a group of Prolific participants who meet the same criteria as you (95% or higher approval rating and at least 100 past studies completed). These participants vary in the following ways:

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 Sciences (such as psychology, economics, history, philosophy)	STEM (such as science, technology, engineering, or math)

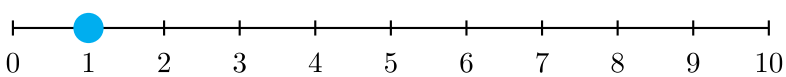
In addition to this information about the candidates, we also have samples of their performance on the technical test. For each candidate, the computer randomly chose two out of the 10 test questions. We can show you how the candidate did on these two questions. For instance:

Sample Performance on Technical Test

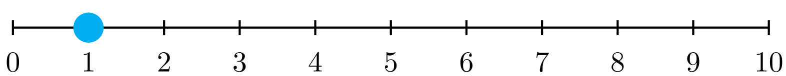
0 out of 2 correct	1 of 2 correct	2 of 2 correct

In the following section, we are interested in your beliefs about the performance of different candidates on this technical test.

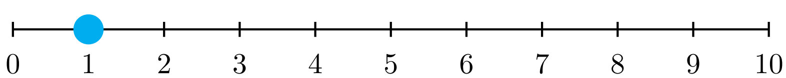
What do you think the average score on the technical test was for **men**?



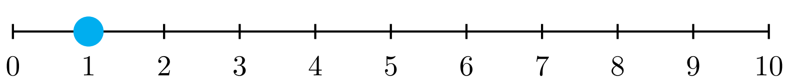
What do you think the average score on the technical test was for people **younger than 45**?



What do you think the average score on the technical test was for **people whose favorite subject is the humanities (such as writing, languages, art)**?



What do you think the average score on the technical test was for **people who have an advanced degree**?



What do you think the average score on the technical test was for **people whose favorite subject is STEM (such as science, technology, engineering, or math)**?

0 1 2 3 4 5 6 7 8 9 10

What do you think the average score on the technical test was for **women**?

0 1 2 3 4 5 6 7 8 9 10

What do you think was the average test score for people **45 and older**?

0 1 2 3 4 5 6 7 8 9 10

What do you think the average score on the technical test was for **people whose highest degree is a bachelor's degree**?

0 1 2 3 4 5 6 7 8 9 10

What do you think the average score on the technical test was for **people whose favorite subject is social science (such as psychology, economics, history, philosophy)**?

0 1 2 3 4 5 6 7 8 9 10

What do you think the average score on the technical test was for **people who have a high school degree or less**?

0 1 2 3 4 5 6 7 8 9 10

The Resumes (Blind Recruiters)

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

Educational Attainment

High School Degree or Less	Bachelor's Degree	Advanced Degree

Favorite Subject

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

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

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

The Resumes (Non Blind Recruiters)

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 Sciences (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

Evaluating Resumes: Your Choices

You'll evaluate five different resumes and make choices based on a list of rows. We are trying to understand your preferences, so we will ask you to make decisions for each row:

- Each row has two options: **Hire** or **Do Not Hire** the candidate.
- In the first row, if you decide to hire the candidate you can earn 50 cents for each answer the candidate got right on the 10-question test. If you decide not to hire, you can earn 50 cents for sure.

- In the next row, you can decide to hire and earn 50 cents for each right answer, or not hire and earn $1.00 for sure.
- Keep making these choices for each row.
- Once you decide not to hire the candidate in a given row, you can choose **Do Not Hire** in all remaining rows, because the earnings associated with not hiring the candidate increase with each row.

Remember:

- When you choose to hire in a row, your bonus depends on how well the candidate did on the test. It could be anything from $0 (if they got 0/10 questions correct) to $5 (if they got 10/10 questions correct).
- You will only get these extra payments if you are among the **10% of recruiters** who are randomly chosen.

This is what a list looks like:

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
50 cents for each question answered correctly	400 cents Total
50 cents for each question answered correctly	450 cents Total
50 cents for each question answered correctly	500 cents Total
50 cents for each question answered correctly	550 cents Total
50 cents for each question answered correctly	600 cents Total
50 cents for each question answered correctly	650 cents Total
50 cents for each question answered correctly	700 cents Total
50 cents for each question answered correctly	750 cents Total
50 cents for each question answered correctly	800 cents Total
50 cents for each question answered correctly	850 cents Total
50 cents for each question answered correctly	900 cents Total
50 cents for each question answered correctly	950 cents Total
50 cents for each question answered correctly	1000 cents Total
50 cents for each question answered correctly	1050 cents Total

About the Candidates

The resumes you'll evaluate are from real Prolific candidates. These candidates took a test and answered resume questions as part of a separate study. They've all done at least 100 studies on Prolific and have a 95% or higher approval rate.

Your Pay

Completing the study guarantees you $3. If you are selected to receive a bonus payment, your bonus payment depends on your hiring decisions.

After all recruiters and candidates are done with the study, you'll be paired with a real candidate whose resume matches ONE of the five you'll have evaluated. For that resume, the computer will randomly select one row in the list to decide what happens. Here's how it works:

- If you chose to **hire** the candidate in that row, you'll earn 50 cents for every right answer they gave on their test.
- If you chose **NOT to hire** the candidate in that row, you'll receive the fixed payment from that row.

Remember, your choice to hire impacts the candidate. If you hire them, they'll get an extra 100 cents.

Understanding Question: If you are selected for extra payment and you chose to hire the candidate from the computer's chosen row, what bonus payment will you receive?

- ☐ $0
- ☑ 50 cents ($0.50) per questions answered correctly by the candidate I matched with
- ☐ 100 cents ($1) per questions answered correctly by the candidate I matched with

Resume X out of 5:

Blind Recruiters

- Educational Attainment: **Bachelor's Degree**
- Favorite Subject: **Social Science (such as psychology, economics, history, philosophy)**
- Sample Performance on Technical Test: **1 of 2 correct**

Non Blind Recruiters

- Age: **Under 45 years old**
- Gender: **Man**
- Educational Attainment: **Bachelor's Degree**
- Favorite Subject: **Social Science (such as psychology, economics, history, philosophy)**
- Sample Performance on Technical Test: **1 of 2 correct**

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
50 cents for each question answered correctly	400 cents Total
50 cents for each question answered correctly	450 cents Total
50 cents for each question answered correctly	500 cents Total
50 cents for each question answered correctly	550 cents Total
50 cents for each question answered correctly	600 cents Total
50 cents for each question answered correctly	650 cents Total
50 cents for each question answered correctly	700 cents Total
50 cents for each question answered correctly	750 cents Total
50 cents for each question answered correctly	800 cents Total
50 cents for each question answered correctly	850 cents Total
50 cents for each question answered correctly	900 cents Total
50 cents for each question answered correctly	950 cents Total
50 cents for each question answered correctly	1000 cents Total
50 cents for each question answered correctly	1050 cents Total

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 show that you read our questions carefully, please enter twenty as your answer to the following question.

How many resumes did you just evaluate?

Now, we would like to ask several questions about you

Generally speaking, are you a person who is willing to take risks or do you try to avoid risks? *Please use a scale from 0 to 10, where a 0 means you are "completely unwilling to take risks" and a 10 means you are "very willing to take risks."*

0 1 2 3 4 5 6 7 8 9 10

In comparison to others, are you a person who is generally willing to give up something today in order to benefit from that in the future or are you not willing to do so?
Please use a scale from 0 to 10, where a 0 means you are "completely unwilling to give up something today" and a 10 means you are "very willing to give up something today."

0 1 2 3 4 5 6 7 8 9 10

How do you assess your willingness to share with others without expecting anything in return when it comes to charity?
Please use a scale from 0 to 10, where 0 means you are "completely unwilling to share" and a 10 means you are "very willing to share." You can also use the values in between to indicate where you fall on the scale.

0 1 2 3 4 5 6 7 8 9 10

About Yourself

As a final step, please take a few moments now to answer some brief questions about yourself.

How do you identify?

- ☐ Man
- ☐ Woman
- ☐ Non-binary/third gender
- ☐ Prefer to self-describe ______
- ☐ Prefer not to say

What is your age?
______

What is your race? Please select all that apply.

- ☐ White
- ☐ Black or African American
- ☐ American Indian or Alaska Native
- ☐ Asian or Asian American
- ☐ Native Hawaiian or Pacific Islander
- ☐ Some other race (please specify) ______
- ☐ Prefer not to say

Are you of Hispanic, Latine, or Spanish origin, such as as Mexican, Puerto Rican, or Cuban?

☐ Yes
☐ No

Please select the level of education that you have completed.

☐ High School Degree or Less
☐ Bachelor's Degree
☐ Advanced Degree

Which is your favorite subject?

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

Thanks for answering these questions! As a final step, please answer the question below before finishing the survey.

On a scale of 1 – 7, please indicate how easy or difficult you found the instructions. Please note that your answer to this question will not impact your chances of receiving a bonus payment.

◯	◯	◯	◯	◯	◯	◯
Very Easy	Easy	Somewhat Easy	Neither Easy nor Difficult	Somewhat Difficult	Difficult	Very Difficult

F.1.1 Candidate Survey

What is the purpose of this research?

In this academic study, we are interested in understanding the dynamics of job search. You will be serving as a potential job candidate in this study. Our goal is to understand your willingness to apply to different job opportunities.

What can I expect if I take part in this research?

You will complete an online survey. It should take you no more than 25 minutes.

You will have no direct interaction with any other participant, but the decisions you make may impact the earnings of other participants in a different part of the study. In addition, your responses in this study will be anonymized and may be used in another study where other participants will view them. These participants will not receive identifying information about you, and you will not receive identifying information about them. You will be told how your decisions may impact the earnings of other participants.

You will earn $5 guaranteed for completing the study. This payment will be made to you through the Prolific platform within 48 hours of your participation. In addition, you have the opportunity to earn up to $1.25 in bonus pay.

Your answers will be linked to your Prolific ID at the time of the study. However, we will delete your Prolific ID from the stored dataset after completing study payments. Only data without your Prolific ID will be analyzed or shared. No other identifying information will be collected.

This survey contains understanding and attention questions. If you answer an understanding question incorrectly, or if you fail to answer an attention question within the given time frame, you may be dismissed from the study and may not receive payment. For that reason, you should read the instructions carefully and should not navigate away from the survey page during your participation.

What should I know about a research study?

- Whether or not you take part is up to you.
- Your participation is completely voluntary.
- You can choose not to take part.
- You can agree to take part and later change your mind.
- Your decision will not be held against you.
- Your refusal to participate will not result in any consequences or any loss of benefits that you are otherwise entitled to receive.
- You can ask all the questions you want before you decide.

You may not be told everything

As part of this research design, you may not be told everything about the purpose of this study. In addition, while you will have complete and truthful information about the procedures of the version of the study that you are participating in, there may be other versions of the study with different procedures. You will not be told about these other versions.

Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at Katherine Coffman, Harvard Business School, 617 495 6538 or kcoffman@hbs.edu.

Overview

Thank you for participating today!

In this study, we're exploring job search dynamics. **You'll play the role of a job candidate.** Our aim is to understand how willing you are to apply to various job opportunities.

You will earn $5 for sure for finishing this study.

You will make several decisions in this study that can impact your bonus payment. At the very end of the study, the computer will select at random **one decision** you made as the **"decision-that-counts for bonus."** We will use the choice you made for this question to determine your bonus payment.

About You

First, we would like to ask you some brief questions about yourself.

What is your age?

[ ]

How do you identify?

- ☐ Man
- ☐ Woman
- ☐ Non-binary/third gender
- ☐ Prefer to self-describe [ ]

Which is your highest educational attainment?

- ☐ High School Degree or Less
- ☐ Bachelor's Degree
- ☐ Advanced Degree

How would you describe your favorite subject?

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

(End of About You page)

The Technical Test

Now, please answer 10 multiple-choice questions assessing your coding and programming skills. These questions relate to a job opportunity that we will describe after the test. If one of these questions is the decision-that-counts for bonus, you will earn $1 if you answered it correctly.

You have **3 minutes** to take the test. All questions are on one page. Once the 3 minutes are up, you'll move to the next page of the survey automatically.
Click the arrow to start the test.

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

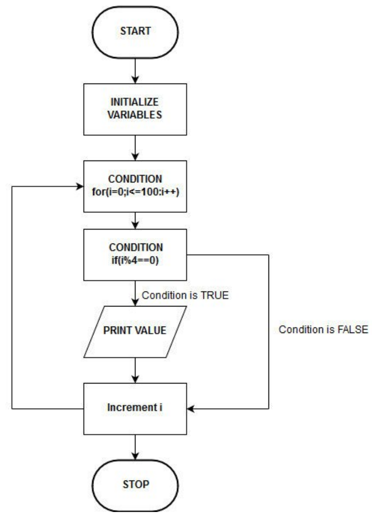
```
0001001001000101
0010010011101100
10101101001...
```

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>
```

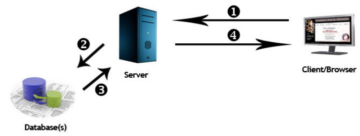
What is its output?

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

Please wait until time has expired to continue.

Your Test Performance

What do you think was your score on the test? If this question is chosen as the decision-that-counts for bonus, you will earn $1 if you guess your score correctly.

Willingness To Apply

In this part of the study, we want to understand how willing you are to apply to a job opportunity.

Please read the instructions carefully.

Recruiter Evaluations

Before you joined this study, we asked other Prolific participants to act as recruiters for a job opportunity. We showed them several example candidate resumes. Each resume included personal information about the candidate and partial information about the candidate's performance on the test you just took.

For each candidate, recruiters had to decide how willing they would be to hire a candidate with that resume. Recruiters were more willing to hire candidates that they thought had strong test scores.

Your Decision

Now, we want to understand how willing you would be to apply for this "job opportunity." You will make a series of choices, like in the list below. In each row of the list, you will have two options to choose from:

- **Apply:** you can get 100 cents ($1) in extra pay, but only if a recruiter who saw your resume wanted to hire you.
- or **Do not apply:** you can get a fixed payment that doesn't depend on your resume or the recruiter's decision. This fixed payment will increase as you go down the list, from 5 cents ($0.05) up to 125 cents ($1.25) for sure.

Note that this job opportunity requires no additional work. It is just a chance for additional pay.

This is what a list looks like:

APPLY	**DO NOT APPLY**
100 cents only if you are hired	5 cents for sure
100 cents only if you are hired	10 cents for sure
100 cents only if you are hired	15 cents for sure
...	...
100 cents only if you are hired	125 cents for sure

Your Resume

Here is your resume for this job opportunity. It includes the following personal information you provided and a sample of your test performance–your performance on two random questions picked by the computer. We showed this exact resume to recruiters. They decided whether or not they would be willing to hire you:

(Non Blind Resume)

- Age: **Under 45 years old**
- Gender: **Woman**
- Educational Attainment: **Advanced Degree**
- Favorite Subject: **Humanities (such as writing, languages, art)**
- Sample Performance on Technical Test: **Your score on 2 questions picked at random**

Remember that this is what your resume looks like:

- Age: **Under 45 years old**
- Gender: **Woman**
- Educational Attainment: **Advanced Degree**
- Favorite Subject: **Humanities (such as writing, languages, art)**
- Sample Performance on Technical Test: **Your score on 2 questions picked at random**

Now, decide how willing you are to apply with this resume by completing the list below:

If this question is the decision-that-counts for bonus, the computer will pick a random row and implement your choice for that row. In that case, if you choose to apply, you will be hired only if a randomly chosen recruiter who saw your exact resume chose to hire you. If you choose to not apply, you will receive the fixed payment from that row.

APPLY	**DO NOT APPLY**
100 cents only if you are hired	5 cents for sure
100 cents only if you are hired	10 cents for sure
100 cents only if you are hired	15 cents for sure
100 cents only if you are hired	20 cents for sure
100 cents only if you are hired	25 cents for sure
100 cents only if you are hired	30 cents for sure
100 cents only if you are hired	35 cents for sure
100 cents only if you are hired	40 cents for sure
100 cents only if you are hired	45 cents for sure
100 cents only if you are hired	50 cents for sure
100 cents only if you are hired	55 cents for sure
100 cents only if you are hired	60 cents for sure
100 cents only if you are hired	65 cents for sure
100 cents only if you are hired	70 cents for sure
100 cents only if you are hired	75 cents for sure
100 cents only if you are hired	80 cents for sure
100 cents only if you are hired	85 cents for sure
100 cents only if you are hired	90 cents for sure
100 cents only if you are hired	95 cents for sure
100 cents only if you are hired	100 cents for sure
100 cents only if you are hired	105 cents for sure
100 cents only if you are hired	110 cents for sure
100 cents only if you are hired	115 cents for sure
100 cents only if you are hired	120 cents for sure
100 cents only if you are hired	125 cents for sure

Understanding Question: What information was on your resume for this opportunity?

Your favorite subject
Your educational attainment
Sample performance on technical test

Your favorite subject
Your educational attainment
Your age
Sample performance on technical test
Your gender

That's correct! Please click the arrow to continue.

Updated Resume

Thank you for making your application decision.

We've now created an updated version of your resume. It includes everything that was on your previous resume, **except now it no longer includes your age and gender**. We also showed this exact resume to recruiters in the previous study. They decided whether or not they would be willing to hire you:

- Educational Attainment: **Advanced Degree**
- Favorite Subject: **Humanities (such as writing, languages, art)**
- Sample Performance on Technical Test: **Your score on 2 questions picked at random**

Remember that this is what your resume looks like:

- Educational Attainment: **Advanced Degree**
- Favorite Subject: **Humanities (such as writing, languages, art)**
- Sample Performance on Technical Test: **Your score on 2 questions picked at random**

Now, you can decide whether you would want to apply with this resume by completing the list below.

If this question is the decision-that-counts for bonus, the computer will pick a random row and implement your choice for that row. In that case, if you choose to apply, you will be hired only if a randomly chosen recruiter who saw your exact resume chose to hire you. If you choose to not apply, you will receive the fixed payment from that row.

APPLY	DO NOT APPLY
100 cents only if you are hired	5 cents for sure
100 cents only if you are hired	10 cents for sure
100 cents only if you are hired	15 cents for sure
100 cents only if you are hired	20 cents for sure
100 cents only if you are hired	25 cents for sure
100 cents only if you are hired	30 cents for sure
100 cents only if you are hired	35 cents for sure
100 cents only if you are hired	40 cents for sure
100 cents only if you are hired	45 cents for sure
100 cents only if you are hired	50 cents for sure
100 cents only if you are hired	55 cents for sure
100 cents only if you are hired	60 cents for sure
100 cents only if you are hired	65 cents for sure
100 cents only if you are hired	70 cents for sure
100 cents only if you are hired	75 cents for sure
100 cents only if you are hired	80 cents for sure
100 cents only if you are hired	85 cents for sure
100 cents only if you are hired	90 cents for sure
100 cents only if you are hired	95 cents for sure
100 cents only if you are hired	100 cents for sure
100 cents only if you are hired	105 cents for sure
100 cents only if you are hired	110 cents for sure
100 cents only if you are hired	115 cents for sure
100 cents only if you are hired	120 cents for sure
100 cents only if you are hired	125 cents for sure

We showed you two different resumes. Which one do you think a recruiter would be more likely to hire?

○	○	○	○	○	○	○
Much more likely when my resume **INCLUDES** age and gender	More likely when my resume **INCLUDES** age and gender	Somewhat more likely when my resume **INCLUDES** age and gender	No difference	Somewhat more likely when my resume does **NOT INCLUDES** age and gender	More likely when my resume does **NOT INCLUDES** age and gender	Much more likely when my resume does **NOT INCLUDES** age and gender

What do you think is the overall percentage of candidates hired when resumes **did NOT include** age and gender?

10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

(The "next" arrow will work after you move the slider)

What do you think is the overall percentage of candidates hired when resumes **included** age and gender?

10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

(The "next" arrow will work after you move the slider)

We would now like you to focus on the version of your **resume that does not include your age and gender**. The questions below ask you about your choices for this version of your resume.

- Educational Attainment: **Advanced Degree**
- Favorite Subject: **Humanities (such as writing, languages, art)**
- Sample Performance on Technical Test: **Your score on 2 questions picked at random**

How likely do you think a recruiter was to hire someone with this exact resume?

10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

(The "next" arrow will work after you move the slider)

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?

0 1 2 3 4 5 6 7 8 9 10

Compared to other participants, how qualified do you feel for this opportunity?

Not at all qualified	Very unqualified	Somewhat unqualified	Neither qualified nor unqualified	Somewhat qualified	Very qualified	Extremely qualified

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? If you guess correctly and this is the decision-that-counts for bonus, you'll get an extra $1.

☐ 0 correct
☐ 1 correct
☐ 2 correct

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.

Your favorite subject	0
Your sample performance (0, 1, or 2 out of 2 correct)	0
Your highest educational attainment	0
Total	0

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? 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.

Your favorite subject	0
Your sample performance (0, 1, or 2 out of 2 correct)	0
Your highest educational attainment	0
Total	0

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:

- Educational Attainment: **Advanced Degree**
- Favorite Subject: **Humanities (such as writing, languages, art)**
- Sample Performance on Technical Test: **Your score on 2 questions picked at random**

Given the choice they had, they chose **NOT to hire you**.

Please answer the questions below based upon this recruiter choosing NOT to hire you.

Recall that your resume displayed your performance on two random questions of the technical test. How many of these two questions do you think the recruiter saw you got right? If you guess correctly and this is the decision-that-counts for bonus, you'll get $1.

- ☐ 0 correct
- ☐ 1 correct
- ☐ 2 correct

How fair do you feel this rejection was?

○	○	○	○	○	○	○
Completely unfair	Mostly unfair	Slightly unfair	Neither fair nor unfair	Slightly fair	Mostly fair	Completely fair

How likely do you think it is that a different recruiter who saw this same resume of yours chose to hire you?

10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

(The "next" arrow will work after you move the slider)

What do you think is the overall percentage of candidates hired when resumes **included** age and gender?

10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

(The "next" arrow will work after you move the slider)

What do you think is the overall percentage of candidates hired when resumes **did NOT included** age and gender?

10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

(The "next" arrow will work after you move the slider)

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?

0 1 2 3 4 5 6 7 8 9 10

Compared to other candidates in this study, how qualified do you think you are for this opportunity?

Not at all qualified	Very unqualified	Somewhat unqualified	Neither qualified nor unqualified	Somewhat qualified	Very qualified	Extremely qualified
○	○	○	○	○	○	○

How much do you think the different resume components influenced the recruiter's decision **NOT to hire you**? 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.

Your favorite subject	0
Your sample performance (0, 1, or 2 out of 2 correct)	0
Your highest educational attainment	0
Total	0

Please answer the question below. 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 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?

Now that you have received feedback on one of your resumes from one recruiter, we want to ask you about your willingness to apply again.

You will have a chance to make new choices regarding your willingness to apply for each of your resumes.

Revisiting Your Decisions

You will once again make a series of choices, like in the previous lists. We remind you that, in each row of the list, you will have two options to choose from:

- Apply: you can get 100 cents ($1) in extra pay, but only if a recruiter who saw your resume wanted to hire you.
- or Do not apply: you can get a fixed payment that doesn't depend on your resume or the recruiter's decision. This fixed payment will increase as you go down the list, from 5 cents ($0.05) up to 125 cents ($1.25) for sure.

Note that this job opportunity still requires no additional work. It is just a chance for additional pay.

Revisiting the Resume You Received Feedback On

Here we are showing you your resume that does not include your age and gender again. It includes the following personal information you provided and **a new sample of your test performance**–your performance on two random questions picked by the computer.

– Educational Attainment: **Advanced Degree**
– Favorite Subject: **Humanities (such as writing, languages, art)**
– Sample Performance on Technical Test: **Your score on 2 questions picked at random**

Remember that this is what your resume looks like:

– Educational Attainment: **Advanced Degree**
– Favorite Subject: **Humanities (such as writing, languages, art)**
– Sample Performance on Technical Test: **Your score on 2 questions picked at random**

Now, decide how willing you would be to apply again with this resume by completing the list below:

If one of these rows is the decision-that-counts for bonus, the computer will use your choice to determine whether you apply to the opportunity. If you choose to apply, you will be hired if a **NEW** randomly chosen recruiter who saw your exact resume chose to hire you. If you choose to not apply, you will receive the fixed payment from that row.

Revisiting Your OTHER Resume

Now, we are showing you your other resume again. It includes everything that was on your previous resume, except now it includes your age and gender.

– Age: **Under 45 years old**
– Gender: **Woman**
– Educational Attainment: **Advanced Degree**
– Favorite Subject: **Humanities (such as writing, languages, art)**
– Sample Performance on Technical Test: **Your score on 2 questions picked at random**

APPLY	DO NOT APPLY
100 cents only if you are hired	5 cents for sure
100 cents only if you are hired	10 cents for sure
100 cents only if you are hired	15 cents for sure
100 cents only if you are hired	20 cents for sure
100 cents only if you are hired	25 cents for sure
100 cents only if you are hired	30 cents for sure
100 cents only if you are hired	35 cents for sure
100 cents only if you are hired	40 cents for sure
100 cents only if you are hired	45 cents for sure
100 cents only if you are hired	50 cents for sure
100 cents only if you are hired	55 cents for sure
100 cents only if you are hired	60 cents for sure
100 cents only if you are hired	65 cents for sure
100 cents only if you are hired	70 cents for sure
100 cents only if you are hired	75 cents for sure
100 cents only if you are hired	80 cents for sure
100 cents only if you are hired	85 cents for sure
100 cents only if you are hired	90 cents for sure
100 cents only if you are hired	95 cents for sure
100 cents only if you are hired	100 cents for sure
100 cents only if you are hired	105 cents for sure
100 cents only if you are hired	110 cents for sure
100 cents only if you are hired	115 cents for sure
100 cents only if you are hired	120 cents for sure
100 cents only if you are hired	125 cents for sure

Remember that this is what your resume looks like:

– Age: **Under 45 years old**
– Gender: **Woman**
– Educational Attainment: **Advanced Degree**
– Favorite Subject: **Humanities (such as writing, languages, art)**
– Sample Performance on Technical Test: **Your score on 2 questions picked at random**

Now, decide how willing you would be to apply again with this resume by completing the list below:

If one of these rows is the decision-that-counts for bonus, the computer will use your choice to determine whether you apply to the opportunity. If you choose to apply, you will be hired if a **NEW** randomly chosen recruiter who saw your exact resume chose to hire you. If you choose to not apply, you will receive the fixed payment from that row.

APPLY	**DO NOT APPLY**
100 cents only if you are hired	5 cents for sure
100 cents only if you are hired	10 cents for sure
100 cents only if you are hired	15 cents for sure
100 cents only if you are hired	20 cents for sure
100 cents only if you are hired	25 cents for sure
100 cents only if you are hired	30 cents for sure
100 cents only if you are hired	35 cents for sure
100 cents only if you are hired	40 cents for sure
100 cents only if you are hired	45 cents for sure
100 cents only if you are hired	50 cents for sure
100 cents only if you are hired	55 cents for sure
100 cents only if you are hired	60 cents for sure
100 cents only if you are hired	65 cents for sure
100 cents only if you are hired	70 cents for sure
100 cents only if you are hired	75 cents for sure
100 cents only if you are hired	80 cents for sure
100 cents only if you are hired	85 cents for sure
100 cents only if you are hired	90 cents for sure
100 cents only if you are hired	95 cents for sure
100 cents only if you are hired	100 cents for sure
100 cents only if you are hired	105 cents for sure
100 cents only if you are hired	110 cents for sure
100 cents only if you are hired	115 cents for sure
100 cents only if you are hired	120 cents for sure
100 cents only if you are hired	125 cents for sure

Final Questions

Thanks for answering these questions! As a final step, please answer the questions below before finishing the survey.

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?

○	○	○	○	○
Much more when it did not include information about gender	Somewhat more when it did not include information about gender	About the same	Somewhat more when it included information about gender	Much more when it included information about gender

Do you think that, in this study, recruiters were more likely to hire **women** when the resume did not include information about gender or when it did include information about gender?

○	○	○	○	○
Much more when it did not include information about gender	Somewhat more when it did not include information about gender	About the same	Somewhat more when it included information about gender	Much more when it included information about gender

Do you think that, in this study, recruiters were more likely to hire **older workers** when the resume did not include age information or when it did include age information?

○	○	○	○	○
Much more when it did not include information about age	Somewhat more when it did not include information about age	About the same	Somewhat more when it included information about age	Much more when it included information about age

Do you think that, in this study, recruiters were more likely to hire **younger workers** when the resume did not include age information or when it did include age information?

○	○	○	○	○
Much more when it did not include information about age	Somewhat more when it did not include information about age	About the same	Somewhat more when it included information about age	Much more when it included information about age

Generally speaking, are you a person who is willing to take risks or do you try to avoid risks?

Please use a scale from 0 to 10, where a 0 means you are "completely unwilling to take risks" and a 10 means you are "very willing to take risks."

0	1	2	3	4	5	6	7	8	9	10

On a scale of 1 – 7, please indicate how easy or difficult you found the instructions. Please note that your answer to this question will not impact your chances of receiving a bonus payment.

Very Easy	Easy	Somewhat Easy	Neither Easy nor Difficult	Somewhat Difficult	Difficult	Very Difficult

The last few questions ask about your experiences outside of this study.

In general, how much do you worry about being discriminated against in the job market because of your gender?

Not at all worried	Slightly worried	Somewhat worried	Moderately worried	Very worried	Extremely worried	Absolutely worried

In general, how much do you worry about being discriminated against in the job market because of your age?

Not at all worried	Slightly worried	Somewhat worried	Moderately worried	Very worried	Extremely worried	Absolutely worried

Now, we would like to ask you about your opinion regarding hiring processes in general. In particular, we would like to ask your opinion about hiring processes where recruiters do not see applicants' demographic characteristics, such as gender, age, race, etc. compared to hiring processes where recruiters can see candidates' demographic characteristics.

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?

Strongly prefer recruiters able to see my demographic characteristics	Prefer recruiters able to see my demographic characteristics	Somewhat prefer recruiters able to see my demographic characteristics	Indifferent	Somewhat prefer recruiters NOT able to see my demographic characteristics	Prefer recruiters NOT able to see my demographic characteristics	Strongly prefer recruiters NOT able to see my demographic characteristics

Please indicate whether you agree or disagree with the following statements related to including your demographic characteristics (such as my gender, age, or race) on your resume:

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Including my demographic characteristics will help me get an interview.	○	○	○	○	○
Including my demographic characteristics supports diversity, equity, and inclusion in the workplace.	○	○	○	○	○
Including my demographic characteristics allows me to filter out discriminating employers, with whom I'd rather not have an interview anyway.	○	○	○	○	○
Including my demographic characteristics allows me to show a part of my identity that I'm proud of.	○	○	○	○	○
Including my demographic characteristics creates a doubt for me whether the recruiter selected me for my competence rather than my identity.	○	○	○	○	○

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?

○	○	○	○	○
A lot better if they knew my demographic information	Somewhat better if they knew my demographic information	Indifferent	Somewhat better if they didn't know my demographic information	A lot better if they didn't know my demographic information

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?

○	○	○	○	○
A lot better if they knew my demographic information	Somewhat better if they knew my demographic information	Indifferent	Somewhat better if they didn't know my demographic information	A lot better if they didn't know my demographic information

Please tell us the degree to which you agree or disagree with the following statements:

Hiring processes where the demographic characteristics of applicants are hidden...

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
lead to a more diverse pool of applicants	◯	◯	◯	◯	◯
lead employers to hire a more diverse workforce	◯	◯	◯	◯	◯
lead to a more productive workforce	◯	◯	◯	◯	◯
should be a standard policy for all employers	◯	◯	◯	◯	◯

What is your race? Please select all that apply.

- ☐ White
- ☐ Black or African American
- ☐ American Indian or Alaska Native
- ☐ Asian or Asian American
- ☐ Native Hawaiian or Pacific Islander
- ☐ Some other race (please specify) ________
- ☐ Prefer not to say

Are you of Hispanic, Latin, or Spanish origin, such as as Mexican, Puerto Rican, or Cuban?

- ☐ Yes
- ☐ No

Thank you so much for completing the study. If you would like to optionally provide any comments about the survey or any issues you had while taking the survey, please add them below.