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 in 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, and apply with a non-blind resume that provides a coarse signal of skills alongside gender and age, or a blind resume that hides demographic information. We find that blinding increases the rate at which counter-stereotypical candidates apply. Our study goes beyond initial applications to examine the downstream effects of blinding when candidates receive feedback. We test two competing mechanisms: a discrimination channel, where perceived bias in non-blind rejections discourages future applications, and a quality-signal channel, where blind rejections convey stronger ability signals and induce greater deterrence. We find support for the latter channel. Blind rejections more strongly reduce future applications than non-blind rejections, particularly for women, muting the initial supply-side benefits of blinding.

JEL Classification Numbers: J14, J16, J71

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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, hiring policies that remove applicant identifiers have gained traction as an important tool to increase organizational diversity (Bohnet and Chilazi, 2025).

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 through a large, controlled experiment conducted in a simulated labor market on Prolific with US-based participants. 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 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

[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.

evaluations by age, gender, and regime, conditional on other resume characteristics, we can quantify the extent of discrimination. We find 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 make a series of choices about whether to (i) apply to an opportunity related to those skills or (ii) receive a sure payment, representing an outside option. Across choices, we vary whether candidates would be applying with either a blind or non-blind resume and the attractiveness of the outside option, allowing us to trace out willingness to apply across a range of opportunity costs. 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. On average, candidates are more likely to apply when the process is blind. Although men are equally likely to apply regardless of whether the hiring process is blind or not, women are significantly more willing to apply when the process is blind. Importantly, we observe that willingness to apply is significantly greater among candidates who are arguably stronger: those who perform better on the skills test, whose favorite subject is STEM, and who have higher levels of education. Finally, we find that candidates who anticipate recruiter discrimination based on gender or age exhibit a larger willingness to apply with a blind resume.

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.[3] 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 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.

We find that, after rejection, candidates are significantly less willing to apply again.

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

[3]Throughout the paper and the experiment we frame this as a hiring decision for simplicity, though the closest real-world analogue might be a call back for an interview. In both cases candidates receive a rejection carrying a negative signal.

For men and younger candidates, rejection reduces future willingness to apply, and this drop is similar in magnitude after a blind rejection or a non-blind rejection. Women and older individuals also apply less after rejection. But, for these more counter-stereotypical candidates, blind rejections have a significantly larger deterrence effect compared to non-blind rejections. Together, these results suggest that rejections that could be rationalized by recruiter discrimination have significantly less impact on future application behavior than rejections resulting from a blind hiring process. This seems to operate primarily through rejection's impact on perceived qualifications. Blind rejections lead candidates to more negatively update their perceived skills and qualifications, and these updated beliefs strongly predict their future application decisions.

Rejection type also shapes demand for blinding in future applications. After rejection on a non-blind resume, demand for blinding in future applications increases. This is true regardless of a candidate's age or gender, although the magnitude of the increase is larger for women and older candidates, especially highly productive ones. After a blind rejection, women and older candidates continue to prefer blind applications to non-blind applications. Men, on the other hand, reveal a preference for **non-blind** applications after a blind rejection, and younger individuals become indifferent between blind and non-blind applications. This increase in the demand for non-blind applications is driven by low-productivity men.

How do these differences in demand for blind applications relate to candidates' perceptions of recruiter discrimination? We find that candidates who anticipate recruiter discrimination against their type have a greater demand for applying with a blind resume. 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.

We complement our causal data with survey evidence on demand for non-blind versus blind applications that allows us to speak to a broader set of mechanisms that may drive demand for blinding in external contexts. 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 assess the relative importance of these mechanisms, both within our experimental setting and in the labor market more broadly.Regarding the labor market more broadly, we find that women and respondents concerned about being selected for their identity rather than their competence express a significantly stronger preference for blind applications. Conversely, respondents who agree that revealing their demographic characteristics helps their hiring chances, screen employers, or express their identity report a lower stated preference for blind applications.

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.[4]

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.

[4]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.

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, 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; Angeli et al., 2026).[5]

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

[5]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).

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 (anticipated) discrimination on worker performance has also been shown in other contexts, such as in sports (Parsons et al., 2011; Caselli et al., 2023) and education (Hill and Zhou, 2023; Lepage et al., 2025).

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.

2 Experimental Design

We conduct two large controlled experiments on Prolific in order to study recruiter and candidate behavior. We use the terms "recruiter" to refer to a participant who has been assigned to evaluate resumes and "candidate" to refer to a participant who has been assigned to make application decisions. We frame these decisions in the context of a job opportunity. Figure 1 provides an overview of each study design. Below we describe the main features of both the Recruiter and the Candidate Studies.

2.1 Technical Task, Resumes, and Price Lists

Several design elements are common to both studies; we describe them here to avoid repetition.

The Technical Task. The technical test is a 10-question multiple-choice test that assesses skills related to coding and computer programming. Candidates have three minutes to complete the test during the first part of the candidate study, while recruiters simply see it prior to evaluating candidates based upon their performance.[6]

Candidate Resumes. We use stylized resumes that include candidate-reported information about educational attainment (high school or less, bachelor's, or advanced degree) and favorite subject (humanities, social science, or STEM). The resume also includes a sample of performance on the technical test: the number of correct answers (0, 1, or 2) on two randomly-drawn technical test questions. This provides an informative but imperfect signal of candidate ability, leaving room for potential belief-based discrimination. The non-blind resumes also include gender (man or woman) and age (under 45 years old or 45 years old and above).[7] We chose gender and age as our demographic characteristics of interest, because we hypothesized that they had the potential to generate anticipated and/or observed discrimination. Examples of resumes are provided in Figure A1.

Price Lists. In both studies we use a multiple-price-list design in order to elicit recruiter willingness to hire or candidate willingness to apply at a variety of prices. In each row, participants choose between an action (hiring/applying) and a sure payoff; the sure payoff increases across rows, allowing us to track decisions against a range of outside options.[8] Illustration of the price lists are provided in Figure A2.[9]

2.2 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. Panel A of Figure 1

[6]The full test can be found in the Online Appendix B.

[7]We use only two categories for age and gender to simplify our analysis and reduce the number of potential resumes for recruiters to consider. We only collected non-blind evaluations of men and women in anticipation of statistical power limitations for other gender identities. The 45 year old threshold is close to the median age of the US workforce, 41.8 in 2022, according to BLS.

[8]We programmed the experiments to enforce monotonicity in recruiter and candidates decision-making. That is, once a recruiter (candidate) switched from hire (apply) to not hire (not apply), the price-list auto-filled to not hiring (not applying) for all remaining rows (which offer more attractive outside options). The participant could over-ride this auto-fill by clicking again on the price-list and selecting a new switch point. Note that we also include outside options that strictly dominate the expected payoff to hiring/applying. This feature allows us both to guarantee that even the best possible candidates faced rejection – enabling us to study responses to rejection among an unselected sample – and to naturally screen for comprehension among participants.

[9]Full price lists can be found in the supplementary material.

summarizes the study flow.

We first show recruiters the test to familiarize them with the assessment before reporting their beliefs about 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. This allows us to document stated beliefs about differences in performance across resume characteristics and compare stated beliefs to revealed preferences.[10]

Each recruiter is randomly assigned to either the Blind or Non-Blind treatment and asked to evaluate five resumes. Resumes are randomly-sampled uniformly from the universe of possible resumes (27 possible resumes in the Blind treatment and 108 possible resumes in the Non-Blind treatment). Recruiters complete a price list for each resume. In each row, they decide whether they would prefer to "Hire" the candidate, and receive 50 cents for every technical test question a candidate with that resume answered correctly, or receive a sure payment. The sure payment, representing the recruiter's outside option, increases by \$0.50 across rows, ranging from \$0.50 to \$10.50, while the payoff to hiring the candidate remains fixed across rows. We refer to the highest outside option at which a recruiter is willing to "Hire" a given candidate as their willingness to hire that candidate.

We incentivize recruiters' hiring decisions: 10% of recruiters are randomly selected for bonus payment, matched to a candidate with a resume identical to one they evaluated, and paid according to their choice in a randomly-selected price list 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, limiting the extent to which taste-based discrimination is relevant in our setting. However, recruiters are aware that their hiring decisions may impact candidate payoffs, with hired candidates earning more in expectation. In the final section of the study, recruiters report basic demographics and economic preferences.[11] The study also includes comprehension questions and an attention check (see Appendix A).

2.3 Candidate Study

The primary goal of the Candidate Study is to explore willingness to apply under blind and non-blind hiring processes, and how it evolves after rejection. We incentivize candidates'

[10]We faced a trade-off in the timing of this elicitation. Eliciting beliefs before resume decisions could 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. We do not incentivize these stated beliefs, prioritizing comprehension over incentivization Danz et al. (2022).

[11]Using the methodology of the Falk et al. (2018) paper, we measure risk preferences, patience, and altruism, each on a $0-10$ scale.

decisions 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." Panel B of Figure 1 summarizes the study flow.

We first ask all candidates about their gender, age, education, and favorite subject.[12] At this stage, participants know they will be making application decisions, but they are not explicitly told that these answers will be used to build their stylized resume.

We introduce candidates to the technical test and give them three minutes to complete it.[13] 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, they report their believed score, which is incentivized: candidates earn a $1 bonus if this belief is correct and selected as the decision-that-counts. Note that we do not inform candidates of their actual test score, mirroring many real application contexts in which applicants have only imperfect information about the strength of their candidacy, creating a path through which self-confidence shapes labor market behavior.[14]

Candidates are informed about the Recruiter Study,[15] We implement a within-subjects design, where each candidate is asked their willingness to apply under both a blind and non-blind process, with the order randomized across participants.

For each price list, candidates are shown the resume that would be used for their application, either blind or non-blind.[16] Candidates are not informed about the exact realization of their sample performance, making their believed test score relevant for their application decision, as it likely informs their beliefs about the sample performance score that will be shown. In each row of the price list, the candidate must decide whether they would prefer to "Apply" or receive a sure payment. We increase this outside option by $0.05 across rows, ranging from

[12]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.

[13]The strict timing is designed to reduce candidates' incentive to look up answers. While we cannot fully rule out that some participants "cheat," this seems unlikely to contaminate or confound our primary focus, the treatment differences across blind and non-blind applications.

[14]This design decision aims to simulate the challenge of accurately assessing one's talents in many educational and professional contexts, even in cases where things like grades and test scores are known. Even in information-rich environments, forecasting talent or productivity can be difficult from both the candidate and recruiter perspective.

[15]We explain 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.

[16]Candidates are aware that recruiters reviewed the exact resume they are being asked to apply with; however, we do not provide candidates with information on how reviewers were assigned to blind or non-blind review, making it possible that candidate beliefs about the "types" of recruiters that select into blind review could be relevant for their application decisions.

$0.05 to $1.25. The payoff to applying is $1 if and only if they are hired by their matched recruiter. We refer to the highest price at which a candidate is willing to "Apply" with a given resume as their willingness to apply. Candidates assigned to the Blind (Non-Blind) treatment first complete the price list for that resume, before seeing their updated resume and repeating the application decision.

After providing their willingness to apply for both application types, candidates are randomly assigned (across subjects) to focus on either their Blind or Non-Blind resume and answer questions specific to that version.[17] They report how likely a recruiter would be to hire someone with that resume, how disappointed or frustrated they would feel if rejected (0–10 scale), how qualified they feel relative to others (7-point scale), and their incentivized guess of their sample performance ($1 bonus if they guess correctly and this is the decision-that-counts). They also allocate 100 points across resume features to indicate which characteristics they believe would explain both a hypothetical hire and a hypothetical rejection.

One important goal of our 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 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.

We rely on the dominated rows of recruiters' price lists to provide all candidates with a piece of negative feedback. 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."[18] Importantly, we introduce this key exogenous variation – whether the rejection was blind or

[17]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."

[18]Note that this feedback is quite ambiguous but truthful, as we verified that for every resume in our sample, there was at least one recruiter who chose in at least one row not to hire that resume. We faced a design tradeoff between the informativeness of the feedback and selection into negative feedback; if feedback was highly informative and detailed, this would have introduced significant selection into who received negative feedback. We chose instead to rely on weak feedback, allowing us to study rejection in the full sample, believing this to be the comparative advantage of a controlled study. Given the scarcity of contextual information in the feedback, our "rejection" may best resemble the experience of applying for a position and never hearing back or simply receiving a form-letter rejection.

non-blind – across-subject. Following this feedback, we ask candidates questions related to this negative outcome: believed sample performance, fairness of the rejection (7-point scale), beliefs about hiring likelihood (for themselves and overall), feelings of disappointment and believed qualifications, and their beliefs of how much each feature of their resume contributed to the rejection.

We then re-elicit their willingness to apply with their Blind and Non-Blind resumes, using the same decision structure 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, followed by their willingness to apply with the alternative resume. This within-subject post-rejection elicitation allows us to measure how rejection revises both the level of willingness to apply and the relative demand for blind versus non-blind processes.

In the final portion of the survey, candidates answer questions about their perceptions of blind versus non-blind hiring, both within the context of the experiment and more broadly. Finally, candidates report their race and ethnicity and economic preferences.[19] The study also includes comprehension questions and an attention check (see Appendix A).

2.4 Implementation

We ran the Recruiter Study in June 2024, collecting data from 2,500 Prolific participants, and the Candidate Study shortly after, collecting data from 4,000 participants. We required users to complete the study using a computer rather than a mobile device and restricted participation to those users who had completed at least 100 studies with an approval rating of 95% or above. For the Candidate Study we use Prolific's built-in filters to collect a sample that is balanced on our key demographic variables: we impose that Prolific field 1,000 men aged 45 and above, 1,000 men under 45, 1,000 women aged 45 and above, and 1,000 women under 45.

After applying our pre-registered sample restrictions, detailed in Appendix C, 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 A3. In addition, the full experiment instructions for both the Recruiter Study and the Candidate Study can be found in the supplementary material.

Recruiters receive $3 for completing the 15-minutes study and 10% of recruiters are randomly selected for bonus payment as described above. Candidates receive a $5 comple-

[19] Again using the Falk et al. (2018) 0–10 scale.

tion payment for the 25-minutes study and are incentivized via the decision-that-counts mechanism.[20]

3 Hypotheses

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

3.1 Demand for Blind Applications

First, to establish a baseline pre-rejection, 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 recruiter beliefs in the context of our technical task (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.

3.2 The Impact of Rejection on Willingness to Apply Again

Our primary research question asks how rejection impacts willingness to apply again in the future and relative demand for blind hiring processes. We consider how these impacts

[20]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.

vary both by rejection type (based on a blind or non-blind resume, exogenously varied across-subject) 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 may be stronger for counter-stereotypical candidates (Niederle and Vesterlund, 2007; Coffman, 2014; Cortés et al., 2023; 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.

3.3 Net effects

The third and final objective of this paper is to investigate the total effect of moving from a non-blind to a blind hiring process, factoring in not only impacts on the demand-side (recruiters) but also on the supply- side (candidates). How does a blind hiring process change the applicant pool and the pool of candidates that are ultimately hired? Blinding may improve

the average quality of candidates selected through multiple channels. First, recruiters may hire higher-performing candidates on average when the possibility of age and gender discrimination is eliminated, relying exclusively on other signals of performance. Second, blinding may draw in a larger pool of talented candidates, particularly high quality counter-stereotypical candidates who may have chosen not to apply due to anticipated discrimination in a non-blind hiring process. Our setup allows us to investigate the distribution of performance and the age and gender diversity of the applicant pool and the hired pool under a variety of conditions, including both observed and counterfactual scenarios.

4 Results

We start by exploring candidate behavior, examining demand for blinding, reactions to both blind and non-blind rejections, and mechanisms that can explain these reactions. Then, we turn to recruiter decision-making and compare recruiters' decisions to candidates' beliefs about blind hiring processes. Lastly, we consider the net effects of blind hiring processes in our setting, incorporating both supply and demand-side factors.

4.1 Initial Applications and Demand for Blinding

Our first goal is to document initial willingness to apply among candidates, with a specific focus on demand for blind applications. 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. We measure demand for blinding pre-rejection within-subject, not only to maximize statistical power but also to establish an individual measure of demand-for-blinding that can inform heterogeneity in responses to rejection. Our measure, then, should be interpreted as capturing how an individual adjusts their willingness to apply when explicitly comparing across these two application regimes.

Table 1 predicts an individual's willingness to apply, before rejection, for a given application type, controlling for other resume characteristics. To ease interpretation, we present the effects in standard deviation units.[21] Column 1 of Table 1 reveals no demand for blind applications among young men (coefficient of 0.01 on Blind). Women, on the other hand, have a significantly positive demand for blinding, estimated at 0.07 SDs (significantly greater

[21]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. One standard deviation of willingness to apply corresponds to approximately 28 cents, or equivalently, about 6 price-list rows.

than both 0 and men's estimated demand, 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.[22]

Diving deeper into gaps within application types, we see significant differences in willingness to apply by candidate demographics. Looking first at non-blind decisions, we observe that women are significantly less willing to apply than men (Column 1). On average, women require an outside option of 0.22 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 0.10 SDs. Turning to blind applications, we see that 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).[23]

4.2 Impact of Rejection on Willingness to Apply Again

We find a negative impact of rejection on willingness to apply again. Overall, we observe that individuals are 0.22 SDs less willing to apply post-rejection ($p < 0.01$, Column 1, Table 2). This deterrence effect suggests that despite the feedback being a relatively weak signal (quite ambiguous information about the behavior of one recruiter), candidates are incorporating it into their decision-making.

In Section 3, we hypothesized that, following rejection, candidates' willingness to apply would drop, because negative feedback impacts their beliefs about their own performance and about the overall hiring rate of recruiters. Consistent with this hypothesis, we find that rejection changes candidates' beliefs, primarily about their own chances of being hired. They also revise downward their beliefs about recruiters' overall hiring rates when resumes include information about gender and age (Appendix Table A7).

Figure 2 explores how reductions in willingness to apply depend upon the type of rejection. Panel A plots initial willingness to apply as a benchmark, Panel B plots willingness to apply

[22]In Appendix Table A4, we present an across-subject replication of Table 1 separating observations from the first and second application choices. Because of the individual-level heterogeneity in willingness to apply, we observe standard errors on the blinding coefficients that are approximately 3.5 times larger. The across-subject estimates do still yield a significant gender gap in non-blind willingness to apply (-0.21 and -0.22 SDs, $p < 0.01$), but the blinding effects and their interactions are not statistically distinguishable from zero.

[23]Columns 2 - 5 further break down application decisions by gender and age, showing that willingness to apply seems to be predicted by several candidate characteristics. Across all sub-groups (Columns 2 to 5), we find that willingness to apply is stronger among candidates with higher test scores, greater educational attainment, and whose favorite subject is STEM (relative to both humanities and social sciences). Greater risk tolerance also predicts greater willingness to apply (see Appendix Table A5). Note that for simplicity, our main text presents specifications that analyze the independent impacts of gender and age on willingness to apply. In the Appendix Table A6, we present additional analysis that explores their interaction, estimating effects separately for young men, young women, older men, and older women.

after a non-blind rejection, and 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 test score and other resume characteristics, we estimate that a blind rejection reduces willingness to apply by nearly 40% more than a non-blind rejection (Column 1, Table 2, $p < 0.01$).

These overall drops in willingness to apply mask important heterogeneity in reactions to blind versus non-blind rejections across age and gender (see Figure 2). The relatively larger impact of blind rejections on willingness to apply is driven by counter-stereotypical candidates. As Table 2 shows, women's willingness to apply drops by twice as much after a blind rejection than after a non-blind rejection ($p < 0.01$, Column 3), 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.

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 deterrence effect, particularly for women. Blind rejections widen gender gaps in willingness to apply relative to non-blind rejections (see Appendix Table A8).

4.3 Impact of Rejection on Relative Demand for Blinding

We now consider the impact of rejection on demand for blind applications; 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?

Column 1 of Table 3 shows that, overall, rejection does not significantly impact demand for blinding among young men. However, women and older candidates increase their demand for blinding after rejection ($p < 0.10$ for both effects). Columns 2 and 3 further break down the analysis by rejection type. We observe that non-blind rejections significantly increase demand for blind applications among women, more so than among men (by 0.11 SDs, $p < 0.10$, Column 2 of Table 3) and for older individuals compared to younger individuals (by 0.09 SDs, $p < 0.05$).[24]

A blind rejection, on the other hand, marginally decreases demand for blind application processes. Women and older individuals maintain a similar demand for blinding following a blind rejection (Column 3 of Table 3). But, relative demand for blinding falls among young men ($p < 0.10$). In fact, after being rejected on a blind application, men are significantly

[24]Appendix Figure A4 provides an illustration of these differences in demand for blinding pre-rejection and following rejection on either a non-blind or blind resume.

more willing to apply on non-blind applications than blind applications going forward (see also Figure A4), perhaps anticipating that gender discrimination could benefit them.

From an employer perspective, the supply-side benefits of a blind application process are larger if the switch attracts talented candidates in particular. To explore this, we can look at heterogeneity in the demand for blind applications by candidate ability as measured by score on the technical test. Figure 3 shows demand for blinding among applicants with test scores between 0 - 5, versus 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, both before and after rejection.[25] More formally, Appendix Table A9 explores heterogeneity in the demand for blinding by test score using regression analysis, estimating that every 1-point increase in technical test score increases demand for blinding, both before and after rejection, by approximately 0.02 SDs ($p < 0.01$).[26]

4.4 Mechanisms: Understanding Candidate Decision-Making

We hypothesized that application decisions and preferences for blind versus non-blind applications are related to perceptions of recruiter discrimination, and that candidates' reactions to rejection depend on whether they attribute the outcome primarily to their skills and qualifications or to discrimination. Whereas both explanations are possible following a non-blind rejection, a blind rejection eliminates the discrimination explanation. Therefore, by varying whether the rejection is blind or non-blind across-subject, we introduce exogenous variation in the scope for anticipated discrimination and trace its causal impact on application behavior following rejection. In this section, we relate application decisions, demand for blinding, and impact of rejection to candidate perceptions of recruiter discrimination and perceived qualifications, and we discuss the role of other mechanisms in shaping candidate decision-making.

4.4.1 The role of anticipated discrimination

After deciding their initial willingness to apply both blind and non-blind, respondents are asked to assess their perceived likelihood of being hired when submitting a blind resume versus a non-blind resume. Specifically, they are asked: "We showed you two different resumes.

[25]For a more granular presentation, Appendix Figures **??** and **??** show willingness to apply by treatment and test scores.

[26]While participants in our experiment are not necessarily tech professionals, this heterogeneity result suggests that higher-scoring candidates, who are likely to be more representative of actual applicants in this labor market, drive the effects we document.

Which one do you think a recruiter would be more likely to hire?" Responses are recorded 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. This question enables us to construct a measure of perceived discrimination for all candidates.

Figure 4 shows that women and older candidates are more likely to expect negative discrimination.[27] 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. Conversely, 42% of men (compared to only 19% of women) and 35% of young candidates (compared to only 24% of older candidates) responded that it was at least somewhat likely they had better chances of being hired with the non-blind resume.[28] Similarly, Figure A5 plots the cumulative distribution function of expected net discrimination - the difference in the extent to which a candidate believes their gender (age) will be a reason for rejection as opposed to success. We observe that, pre-rejection, women (older individuals) are more likely to anticipate that their gender (age) reduces their likelihood of being hired.[29]

Table 4 predicts an individual's willingness to apply from their beliefs about discrimination against their type. Column 1 predicts pre-rejection willingness to apply, adding to the regression this anticipated discrimination measure. We see that the more a candidate anticipates discrimination, the greater their relative demand for blind applications pre-rejection (interaction on Blind Application x Anticipated Discrimination, $p < 0.01$). This relationship strongly persists post-rejection (Columns 2 - 3). Individuals who anticipated more discrimination ex-ante are less willing to apply non-blind following rejection and have greater relative demand for blinding. This is true after both a non-blind rejection (Column 2) and a blind rejection (Column 3). In sum, anticipated discrimination strongly predicts demand for blinding, both before and after rejection.

Figure 5 visualizes this evidence. Panel A shows that initial demand for blinding ap-

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

[28]We can also use across-subject data to explore this issue. Individuals were 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 Table A7. Among individuals asked to consider non-blind resumes (Column 2), 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 (Column 3).

[29]This measure is strongly correlated with our main 7-point Likert scale variable (0.26 for gender and 0.33 for age, with $p < 0.01$). Note that this measure of expected net discrimination is only elicited for candidates who are randomly assigned to a non-blind rejection.

plications is significantly positive for candidates who expect negative discrimination. This preference for blinding applications persists after a rejection on non-blind resume (Panel B). However, this preference for blinding applications is somewhat muted following a rejection on a blind resume (Panel C).

We also find that candidates who expect recruiters to *favor* their type have a significant preference for non-blind applications initially (Panel A). After a rejection on a non-blind resume, men who expected to benefit from positive discrimination from recruiters continue to exhibit a significant relative demand for non-blind applications (Panel B). Women, however, become indifferent to applying with a blind or a non-blind resume after rejection on a non-blind resume. The perceived benefits of a non-blind application for candidates who expect positive discrimination largely persist following a rejection on a blind resume (Panel C). We find this result for all types except for women, whose relative preference for non-blind applications becomes statistically insignificant.

We can also link anticipated discrimination to responses to rejection. Figure 6 shows that anticipated discrimination strongly predicts the relatively larger deterrence effects we observe after blind rejections, especially for those who anticipated recruiter discrimination against their type. The figure plots the estimated willingness to apply of candidates as a function of anticipated discrimination, contrasting pre-rejection decisions with decisions following either blind or non-blind rejections.[30] We estimate that, initially, willingness to apply non-blind falls with the extent of anticipated discrimination, while willingness to apply blind does not. The impacts of blind compared to non-blind rejections depend strongly on the degree of anticipated discrimination. Blind rejections have a significantly larger deterrence effect than non-blind rejections because they are particularly discouraging among candidates who anticipate discrimination (i.e., they believed they had a better chance of being hired under a blind process compared to a non-blind process). Among candidates who believed they had a better shot of being hired non-blind compared to blind, blind rejections are, if anything, less discouraging in terms of future applications, especially regarding their willingness to apply again with a non-blind resume.

Finally, we can relate candidates' beliefs about discrimination to overconfidence. 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), among candidates who were randomly assigned to a non-blind rejection. We 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

[30]These estimates come from an OLS specification that includes controls for gender, age, test score, and other resume characteristics.

confidence, is strongly predictive of how much discrimination they perceive against their type.

4.4.2 The role of perceived qualifications

While rejection on a non-blind resume could potentially be explained via discrimination, a blind resume rejection leaves less room for this interpretation. Thus, candidates may interpret blind rejections as stronger signals of their qualifications and skills. Table 5 shows that, indeed, rejections cause candidates to revise down their beliefs of how qualified they are, and this effect is marginally larger after blind rejections (Column 1, $p < 0.10$). This effect is similar for men, women, younger, and older candidates (Columns 2 - 5).[31]

These effects on perceived qualifications are meaningful because of the significant role perceived qualifications play in driving application decisions. Table 6 shows that perceived qualifications strongly predict initial willingness to apply (Column 1) and willingness to apply again after rejection (Columns 2 - 3). Together, our results show that rejection reduces future willingness to apply, in part by reducing perceived qualifications.

4.4.3 Psychological Mechanisms

The experience of a blind or non-blind hiring process, including being rejected under that process, may also trigger different psychological responses among candidates. In this subsection, we briefly discuss our survey evidence on feelings of fairness, frustration, and luck as they relate to application and rejection type.

Firms often introduce blind hiring processes in an attempt to increase fairness (Bohnet and Chilazi, 2025). To probe how the experience of rejection impacts candidate perceptions of fairness, our survey includes an explicit question about how fair candidates believe their rejection was. Individuals rejected based on a blind resume rate their rejection as significantly more fair than individuals rejected based on a non-blind resume ($p < 0.01$). Panel A of Figure A6 shows that this relationship holds among all candidate types: men, women, younger, and older candidates. Following their rejection, we also asked individuals how disappointed or frustrated they felt.[32] Blind rejections lead to significantly less disappointment and frustration than non-blind rejections (($p < 0.05$). Again, this does not vary by gender or age, as illustrated in Panel B of Figure A6.

[31] One unexpected finding that Table 5 reveals is that even prior to rejection, candidates considering their blind application assess themselves as less well-qualified than those considering their non-blind application, with larger effects among women and older individuals. We account for these initial differences in considering differential updating on qualifications after blind and non-blind rejections, but do not have a clear explanation for what drives these initial gaps.

[32] "Having been rejected by this recruiter, how do you rate the disappointment or frustration you feel on a scale from 0 to 10."

Thus, while blind rejections seem to have a more negative impact on candidates' beliefs of their own skills and their willingness to apply again in the future, they do not seem to have greater psychological costs, consistent with findings in the literature on procedural fairness (Brockner and Wiesenfeld, 1996). Interestingly, when asked initially to predict how they would feel if they were to be rejected, candidates anticipate these differences in psychological costs; looking across-subject, candidates asked to imagine being rejected on a blind resume accurately anticipate less frustration compared to those rejected on a non-blind resume. This suggests that (lower) anticipated psychological costs could be another driver of preferences for blind applications.

4.5 External Relevance of Our Findings

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 and to link our results with beliefs, preferences, and behaviors that are relevant outside of our study.

First, we asked candidates whether they prefer their demographic information be included in their job applications (7-point scale). 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. We observe a greater preference for blind hiring processes among women (by 0.6 points, $p < 0.01$, Column 1 of Table 7) 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, 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 and also more than 50% of younger individuals also indicating some degree of worry (see Appendix Figure A7).[33]. We can relate their answers to their demand for blind applications in our experimental context. Panels A and B of Appendix Figure A8 show that candidates who worry about

[33]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."

gender and/or age discrimination in the labor market 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 A12). Average agreement across statements ranged from 2.5 to 3.2. Women are significantly less likely to agree that revealing their demographics would help them get an interview, but significantly more likely to agree that it supports diversity, equity, and inclusion in the workplace, helps screen out discriminating employers, and allows them to signal a source of identity pride. Women are also significantly more likely to agree that being hired under a non-blind process would create doubt as to whether they were hired based on competence or identity. Older individuals are significantly less likely to agree that revealing demographics would help them get an interview or support diversity, equity, and inclusion. 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 A8 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 candidates in our study do not directly interact with recruiters. 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).

4.6 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.[34] We then compare recruiters' discriminatory behaviors with candidates' beliefs about the extent of discrimination. Recall that recruiters were randomly assigned to evaluate either five blinded resumes or five non-blinded resumes. We observe that blinding resumes does not significantly shift willingness to hire on average (see Appendix Table A13),

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

with similar overall hiring rates across the two treatments.

Table 8 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 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 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.[35][36]

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 8, $p < 0.05$). 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 A14 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 8, $p \approx 0.12$). This effect appears to be similar across different performance signals (see Columns 2, 3, and 4 of Appendix Table

[35]While participants in our experiment are not necessarily in tech nor professional hiring managers, their choices track the same characteristics that a real-world hiring manager would likely value for a coding job.

[36]Recall that our primary, pre-registered analysis restricts attention to recruiters who do not select dominated options in the price list, that is, choosing to hire a worker over accepting an outside option that is strictly greater than the payoff to hiring even the best worker (technical test score of 10). While we think these choices most likely reflect confusion, it is possible that a recruiter makes a dominated choice for other-regarding reasons, hoping to benefit a matched worker. To ensure that this exclusion restriction is not distorting our primary recruiter results, we re-ran Columns 3 and 4 of Table 8, eliminating this specific exclusion restriction. This increases the sample from 5,701 to 8,185 but does not meaningfully change the results. Results available upon request.

A14).[37][38]

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 8 uses our candidate data to illustrate how a risk neutral recruiter looking should weight the different resume characteristics to maximize expected earnings. By using 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 7 shows the return to blinding an application in terms of hiring probability,

[37]Appendix Figure A9 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 A14, 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 A15 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 A10 for results on in-group preferences broken down by younger men, younger women, older men, and older women.

[38]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 A16). 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.

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.[39] 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.

4.7 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).[40]

We use our data to simulate the pool of hired candidates under blind and non-blind

[39]This is consistent with past literature suggesting 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 Exley et al. (2025) find that female students expect different returns from signaling their productivity through their grades, specifically because they anticipate labor market discrimination and expect others to make worse inferences about their concealed grades. Deschamps et al. (2026) show that even workers active in the labor market have rather inaccurate predictions of recruiters' preferences.

[40]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.

hiring processes for different levels of market tightness.[41] 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 9 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 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.[42]

5 Conclusion

We explore the impact of blind hiring processes on labor market outcomes, with a particular focus on how blind hiring processes impact the supply of candidates. Our results reveal that counter-stereotypical candidates, in our case women and older workers, are significantly more willing to apply when the hiring process is blind. These results are, in part, driven by anticipated discrimination. Most counter-stereotypical candidates expect

[41] 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.

[42] 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.

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 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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Figure 1. Survey flows

= Incentivized stage

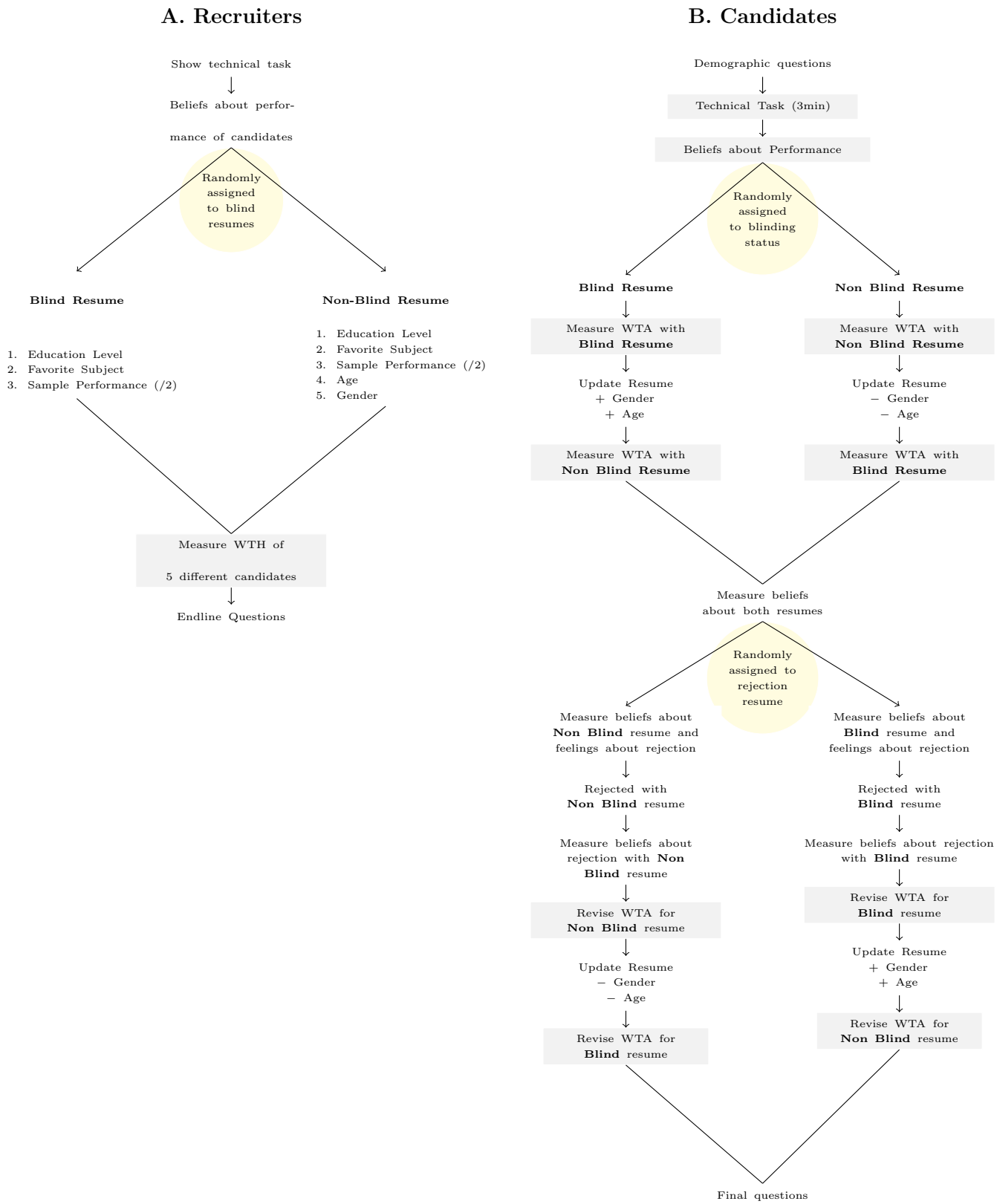
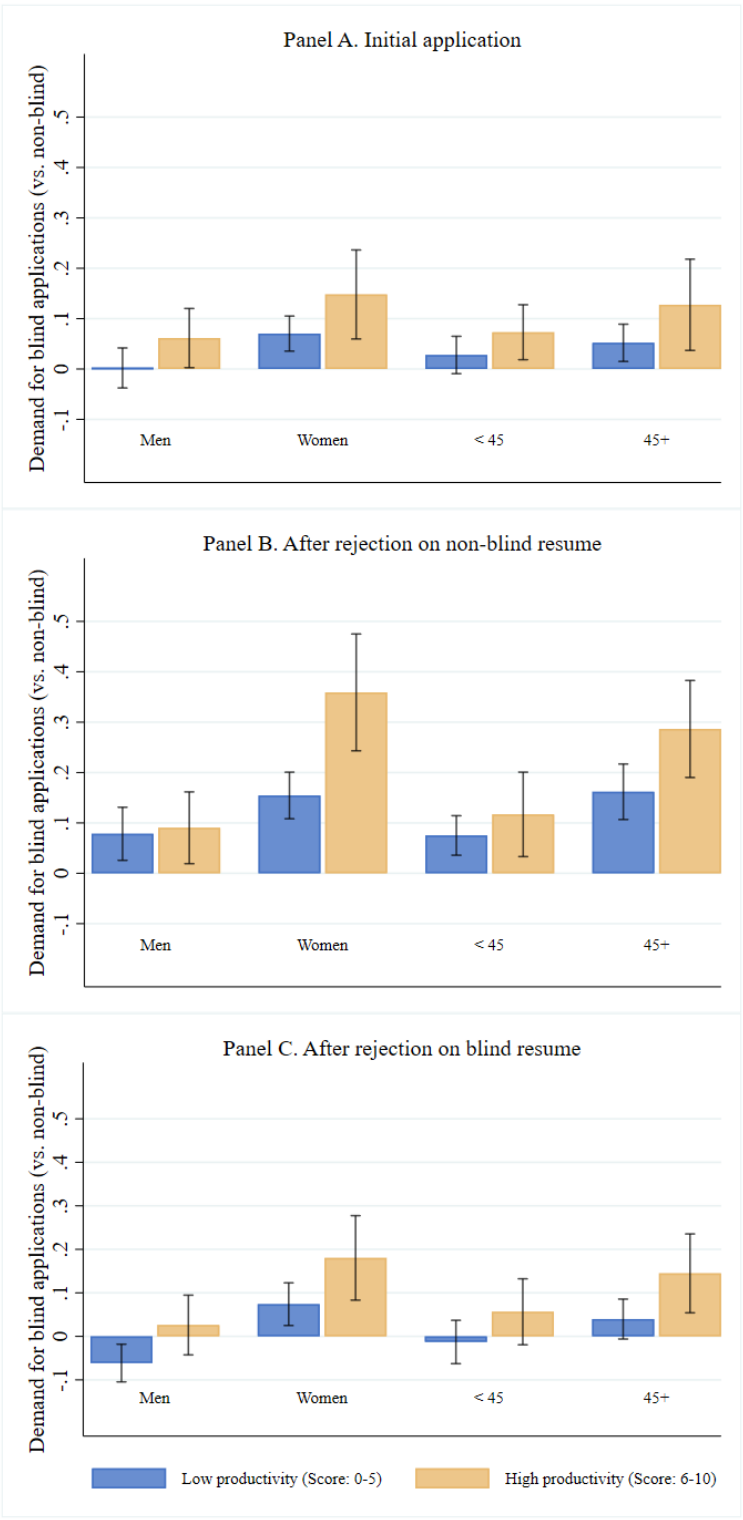


Figure 2. Average Willingness to Apply Before and After Rejection, by Gender and Age

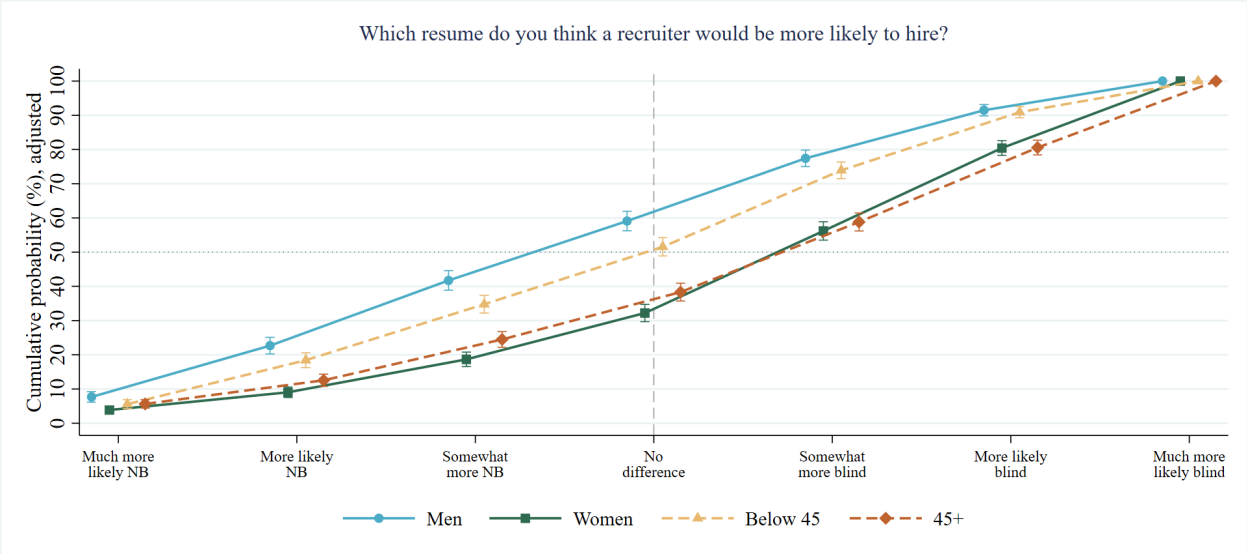
*Notes: Averages are calculated on standardized values. We standardize over the full distribution of all willingness to apply observations, pooling over the four price-lists faced by candidates. Panel A includes applications before rejetion. Panel B includes applications after rejection on a non-blind resume. Panel C includes applications after rejection on a blind resume. Whiskers mark 95% confidence intervals. T-test significance levels: *** p<0.01, ** p<0.05, and * p<0.10.*

Figure 3. Demand for Blind Processes is Strongly Correlated with Productivity



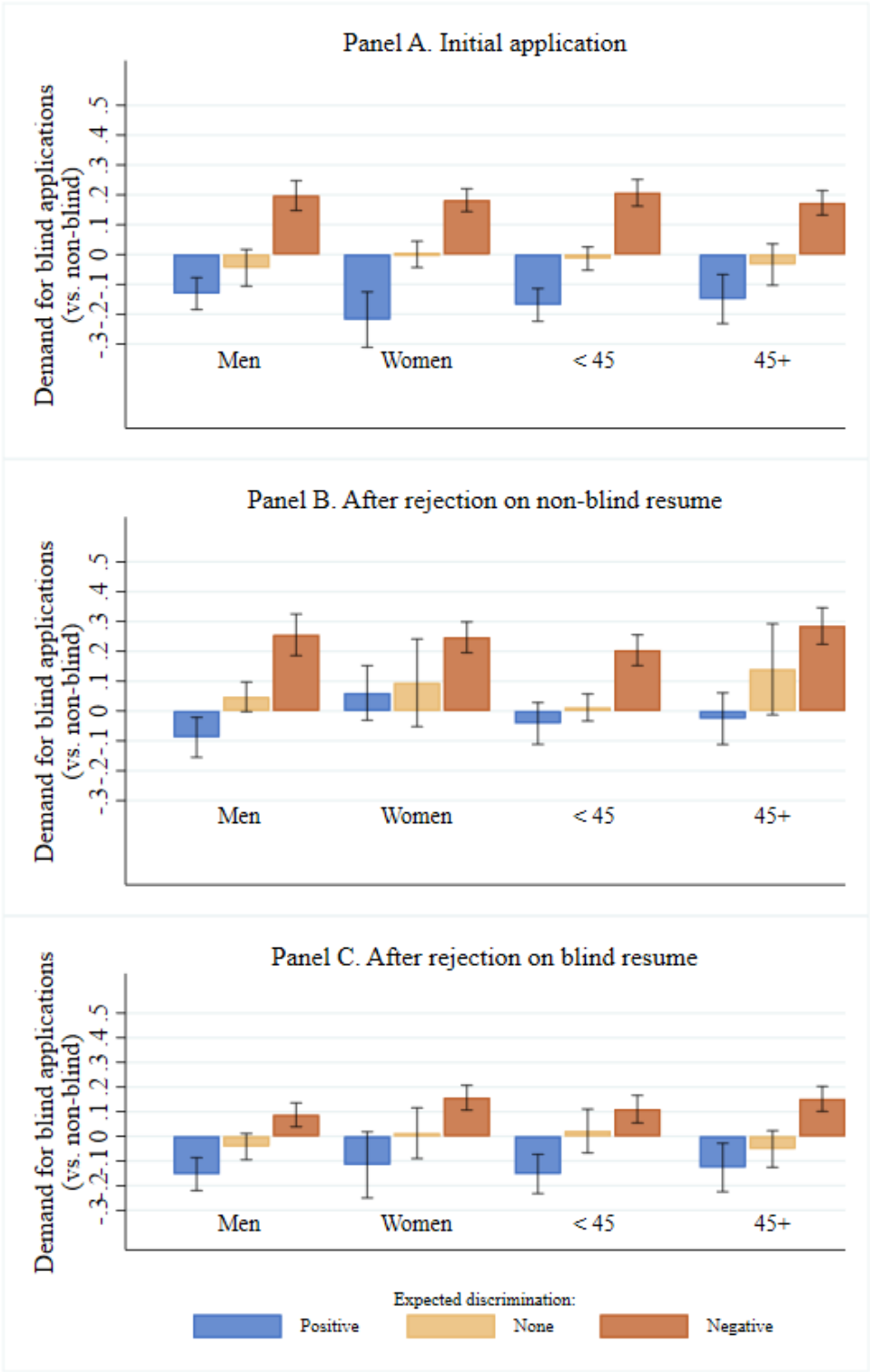
Notes: The figure graphs the estimated demand for blind applications. Demand for blind application is the difference in standardized willingness to apply under a blind process and standardized willingness to apply under a non-blind process, with positive values indicating greater demand for blind applications. Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. Whiskers mark 95% confidence intervals.

Figure 4. Candidates' Expected Gender and Age Discrimination Before Rejection



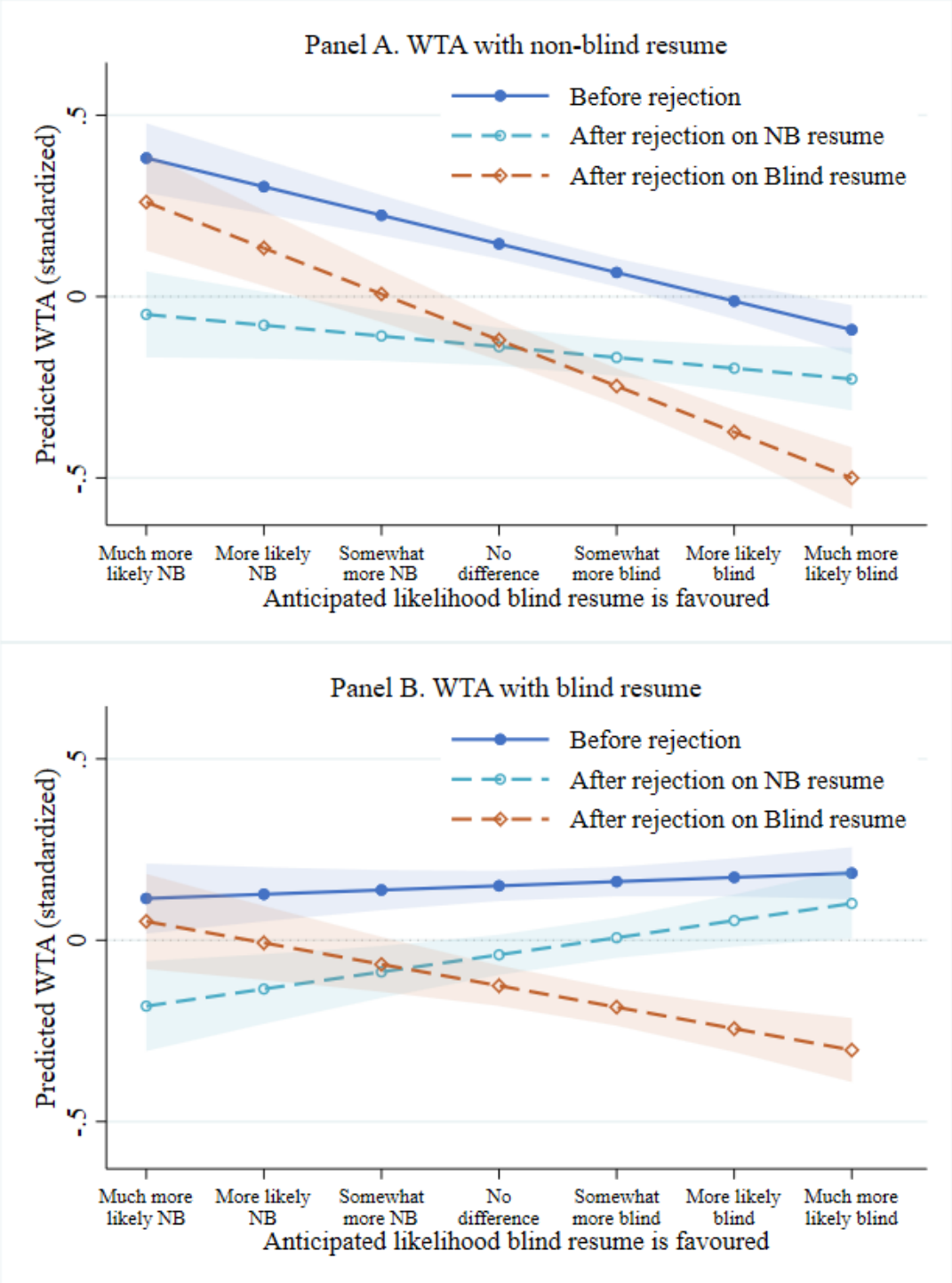
Notes: After they completed the initial two price lists, we asked the following question to candidates: "We showed you two different resumes. Which one do you think a recruiter would be more likely to hire?" Answers on a 7-point Likert scale, from "Much more likely when my resume includes age and gender" to "Much more likely when my resume does not include age and gender." This figure shows adjusted cumulative probabilities from separate binary logit regressions at each response threshold, controlling for test score, subject, and education level. The y-axis shows the predicted probability of responding at or below each category. Whiskers mark 95% confidence intervals.

Figure 5. Demand for Blind Processes is Strongly Correlated with Discrimination Beliefs



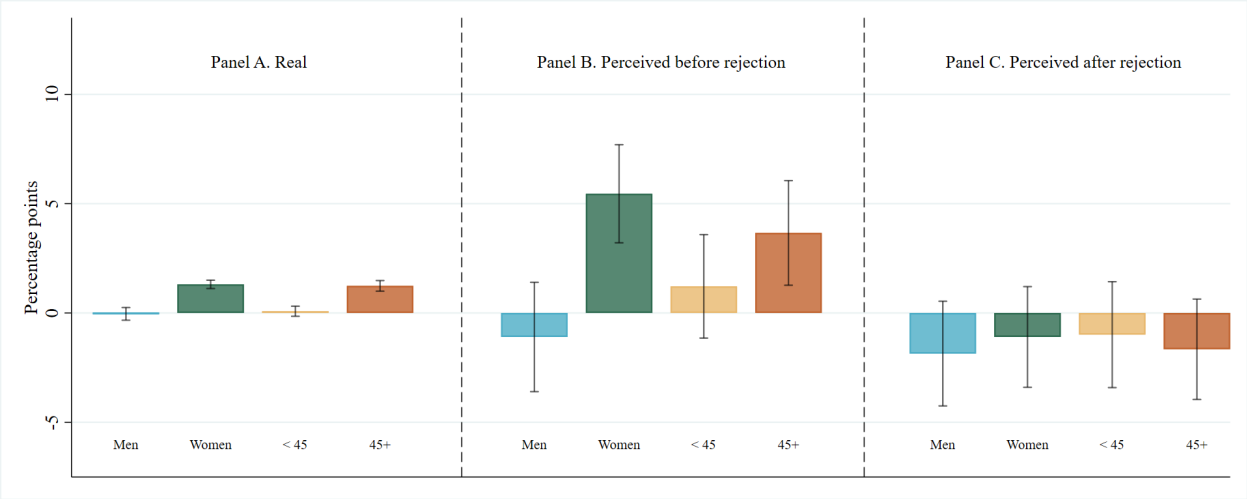
Notes: The figure graphs the estimated demand for blind applications. Demand for blind application is the difference in standardized willingness to apply under a blind process and standardized willingness to apply under a non-blind process, with positive values indicating greater demand for blind applications. Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. Whiskers mark 95% confidence intervals.

Figure 6. Candidates' WTA Before and After Rejection, by Anticipated Discrimination



Notes: This figure 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. Whiskers mark 95% confidence intervals.

Figure 7. 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.

Table 1. Initial Willingness to Apply, 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 application	0.01	-0.00	0.08***	-0.00	0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Women	-0.22***			-0.22***	-0.21***
	(0.04)			(0.06)	(0.06)
Age 45+	-0.10**	-0.09	-0.10*		
	(0.04)	(0.06)	(0.05)		
Blind application × Women	0.06***			0.08***	0.05
	(0.02)			(0.03)	(0.04)
Blind application × Age	0.03	0.04	0.01		
	(0.02)	(0.03)	(0.03)		
Test score	0.07***	0.07***	0.06***	0.09***	0.04***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Favorite subject					
Social sciences	0.03	0.07	0.02	0.01	0.04
	(0.05)	(0.08)	(0.06)	(0.07)	(0.06)
STEM	0.29***	0.34***	0.24***	0.17**	0.39***
	(0.05)	(0.07)	(0.07)	(0.07)	(0.07)
Educational attainment					
Bachelor's degree	0.25***	0.28***	0.22***	0.19***	0.30***
	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)
Advanced degree	0.27***	0.24***	0.29***	0.27***	0.29***
	(0.05)	(0.08)	(0.07)	(0.08)	(0.07)
Observations	4,976	2,318	2,658	2,400	2,576
R^2	0.08	0.07	0.05	0.08	0.08

*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. Clustered standard errors at the candidate level are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table 2. Willingness to Apply 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 3. 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 4. OLS Predicting Willingness to Apply Related to Discrimination Beliefs

Dependent variable:	Willingness to apply (standardized)		
	Initial	After rejection on a	
	Applications	Non-blind resume	Blind resume
	(1)	(2)	(3)
Blind application	-0.37***	-0.22***	-0.29***
	(0.04)	(0.05)	(0.05)
Anticipated discrimination	-0.08***	-0.03**	-0.13***
	(0.01)	(0.02)	(0.02)
Blind application × Anticipated discrimination	0.09***	0.08***	0.07***
	(0.01)	(0.01)	(0.01)
Women	-0.15***	-0.13**	-0.23***
	(0.04)	(0.05)	(0.05)
Age 45+	-0.06	-0.03	-0.08
	(0.04)	(0.05)	(0.05)
Controls			
Test score	X	X	X
Favorite subject	X	X	X
Education	X	X	X
Observations	4,976	2,472	2,504
R^2	0.09	0.09	0.13

*Notes: This table shows coefficient estimates from OLS regressions, where the dependent variable is standardized candidate willingness to apply. Anticipated discrimination is measure on a 7-point Likert scale. 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. OLS Predicting Candidates' Beliefs about Qualifications

Dependent variable:	How qualified				
		By gender		By age	
	All	Men	Women	Below 45	45+
	(1)	(2)	(3)	(4)	(5)
Blind resume	-0.20***	-0.15*	-0.26***	-0.12	-0.27***
	(0.06)	(0.09)	(0.09)	(0.08)	(0.09)
Post-rejection	-0.12***	-0.11***	-0.12***	-0.07**	-0.16***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Blind resume × Post-rejection	-0.06*	-0.06	-0.05	-0.07*	-0.05
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Women	-0.54***			-0.57***	-0.51***
	(0.06)			(0.08)	(0.09)
Age 45+	0.06	0.05	0.06		
	(0.06)	(0.08)	(0.08)		
Controls					
Test score	X	x	X	X	X
Favorite subject	X	X	X	X	X
Education	X	X	X	X	X
Observations	4,976	4,976	4,976	4,976	4,976
R^2	0.20	0.19	0.15	0.20	0.21

*Notes: Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. "How qualified" 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"). We asked all this question 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 6. OLS Predicting Willingness to Apply Related to Qualifications Beliefs

Dependent variable:	Willingness to apply (standardized)		
	Initial	After rejection on a	
	Applications	Non-blind resume	Blind resume
	(1)	(2)	(3)
Blind application	0.03	0.02	0.03
	(0.02)	(0.03)	(0.03)
Qualification beliefs	0.20***	0.19***	0.23***
	(0.01)	(0.02)	(0.02)
Blind application × Qualification beliefs	0.01	0.03***	0.00
	(0.01)	(0.01)	(0.01)
Women	-0.07*	-0.02	-0.20***
	(0.04)	(0.05)	(0.05)
Age 45+	-0.10***	-0.04	-0.13***
	(0.04)	(0.05)	(0.05)
Controls			
Test score	X	X	X
Favorite subject	X	X	X
Education	X	X	X
Observations	4,976	2,472	2,504
R^2	0.18	0.19	0.23

*Notes: 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 7. 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 8. Returns to Resume Characteristics

Dependent variable:	Probability of Being Hired			
	Optimal Risk-Neutral Decisions		Observed Decisions	
	Non-Blind	Blind	Non-Blind	Blind
	(1)	(2)	(3)	(4)
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 9. Comparing Outcomes under Blind and Non-Blind Hiring Processes

	Top Scores (1)	Random (2)	Blind Pre-Rej. (3)	Non-Blind Pre-Rej. (4)	Blind Post-Rej. (5)	Non-Blind Post-Rej. (6)
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 (3) and (4) use candidates' pre-rejection decisions; Columns (5) and (6) use candidates' post-rejection application decisions.

A Additional Figures and Tables

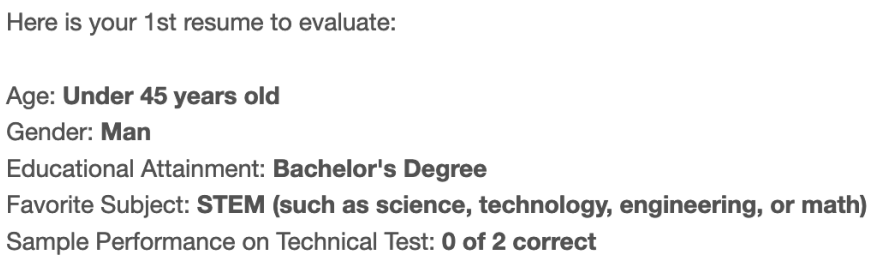
Sample Questions from the Technical Test

1. 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

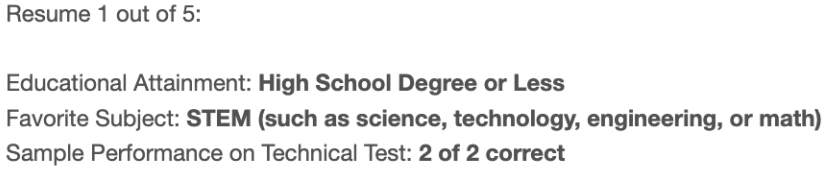
2. If you want to maintain and update a database, which language is typically best to use?
   A. HTML
   B. C++
   C. SQL
   D. Go

Figure A1. Example of Resumes as seen by participants

(a) Non-Blind Resume



(b) Blind Resume



Notes: Both recruiters and candidates saw resumes presented in this format.

Figure A2. Price Lists

(a) Recruiter Study

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

(b) Candidate Study

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**

Notes: "Do not hire" column increases by increments of 50 cents up to 1050 cents. "Do not apply" column increases by increments of 5 cents up to 125 cents

Figure A3. Distribution of Candidate Test Scores, by Gender and Age

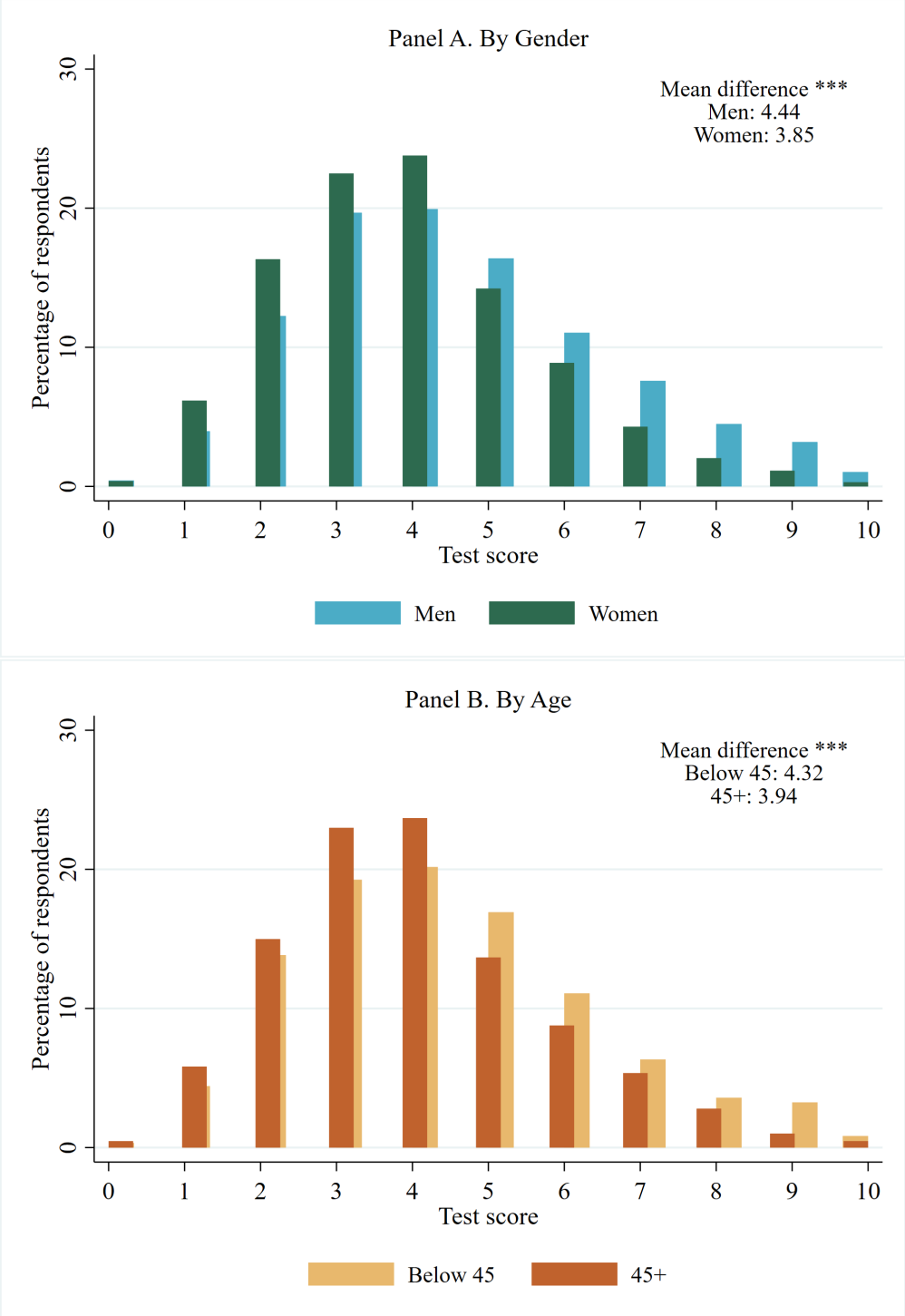
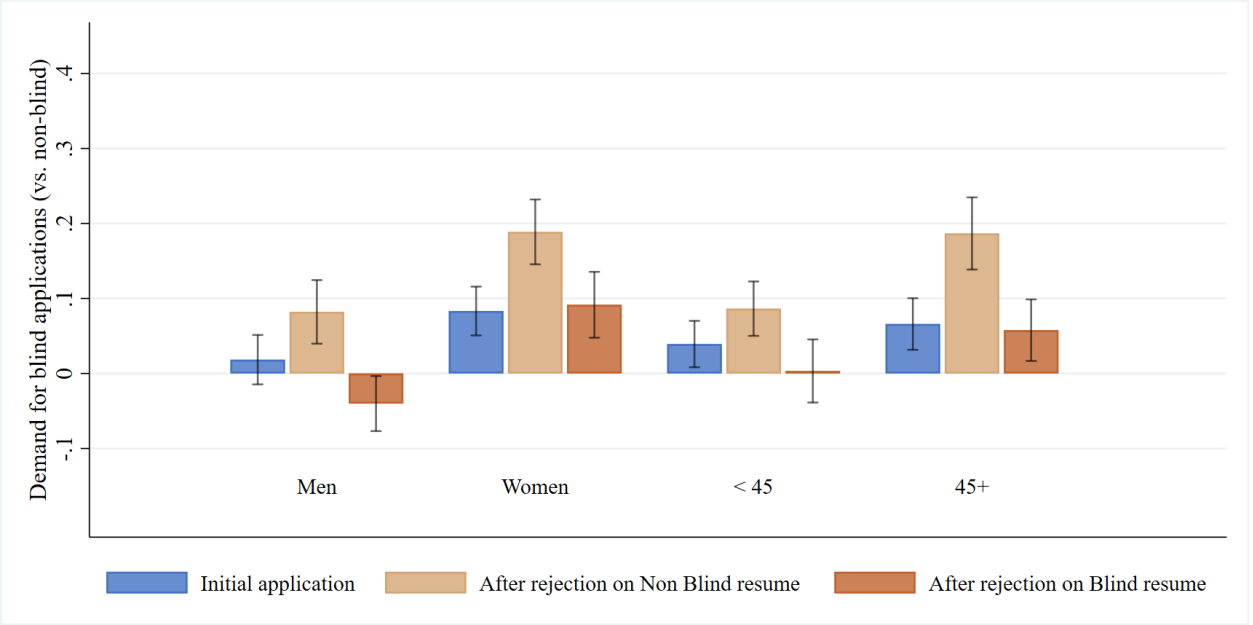
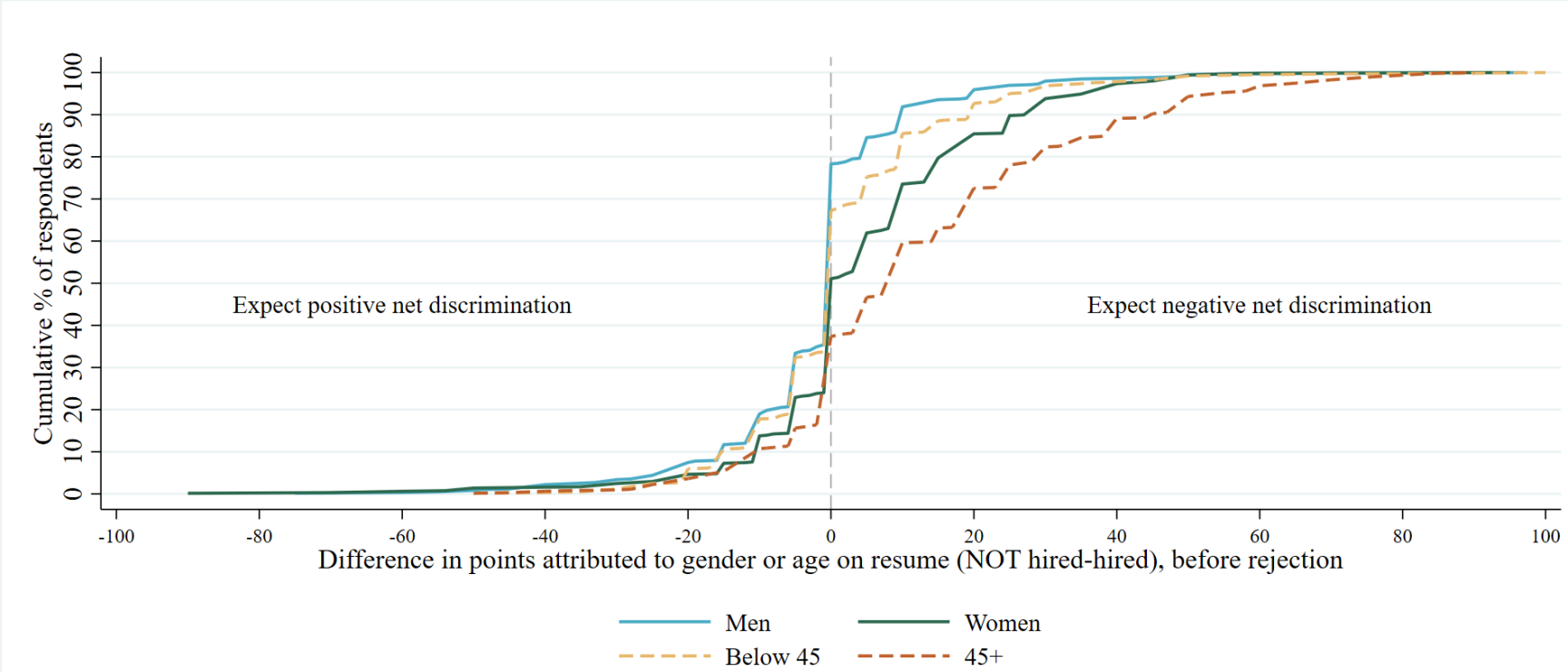


Figure A4. Demand for Blind Processes, Before and After Rejection



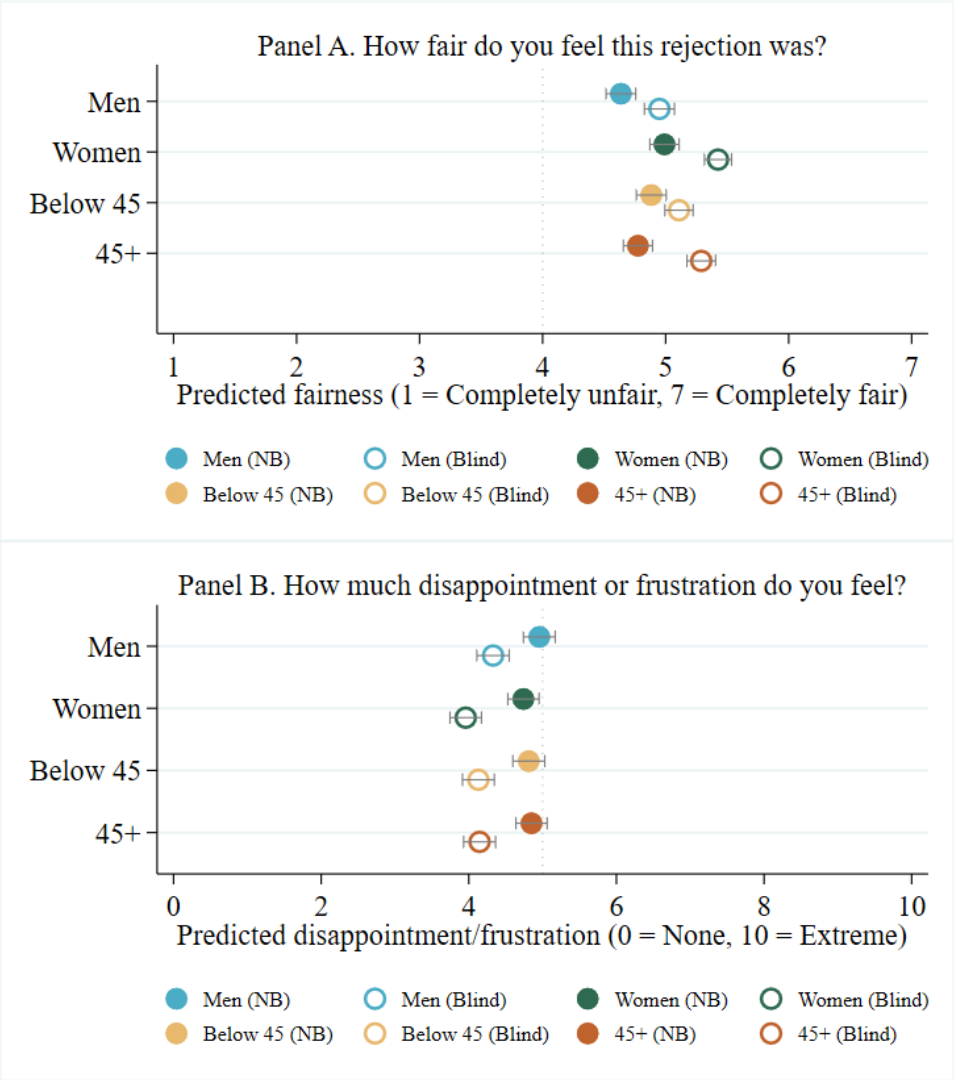
Notes: The figure graphs the average demand for blind applications. Demand for blind application is the difference in standardized willingness to apply under a blind process and standardized willingness to apply under a non-blind process, with positive values indicating greater demand for blind applications. 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. Whiskers mark 95% confidence intervals.

Figure A5. Candidates' Expected Net Gender and Age Discrimination Before Rejection



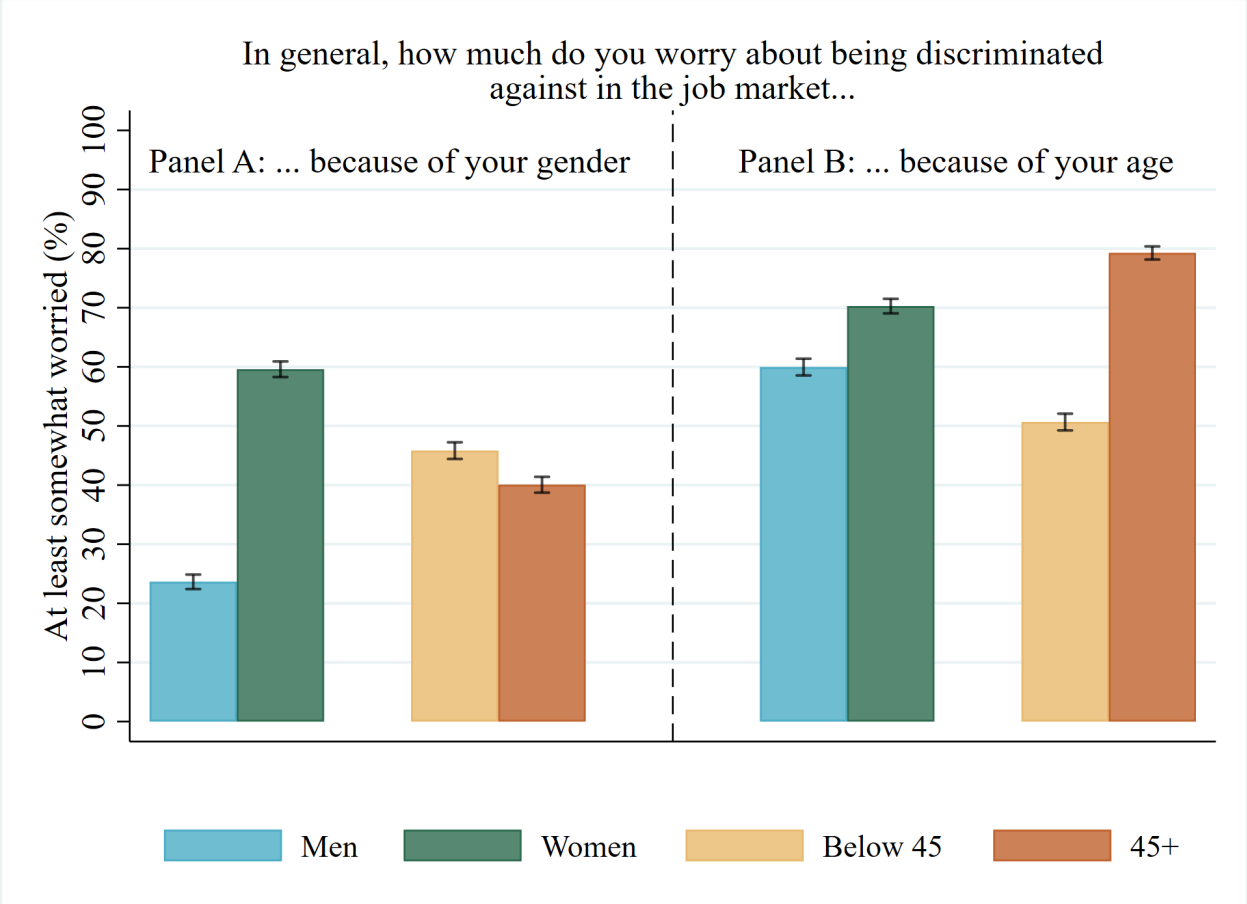
Notes: After they completed the initial two price lists, we asked the following question to candidates, based on the randomly selected resume: "Imagine that a recruiter saw this resume and decided to hire you. How much do you think the different resume components influenced the recruiter's decision? 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 net 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 cumulative distribution function of candidates' answers in the non-blind rejection treatment. (Candidates in the blind rejection treatment were asked to distribute points only across favorite subject, educational attainment, and performance score).

Figure A6. Candidates Perceptions of Fairness and Feelings of Disappointment



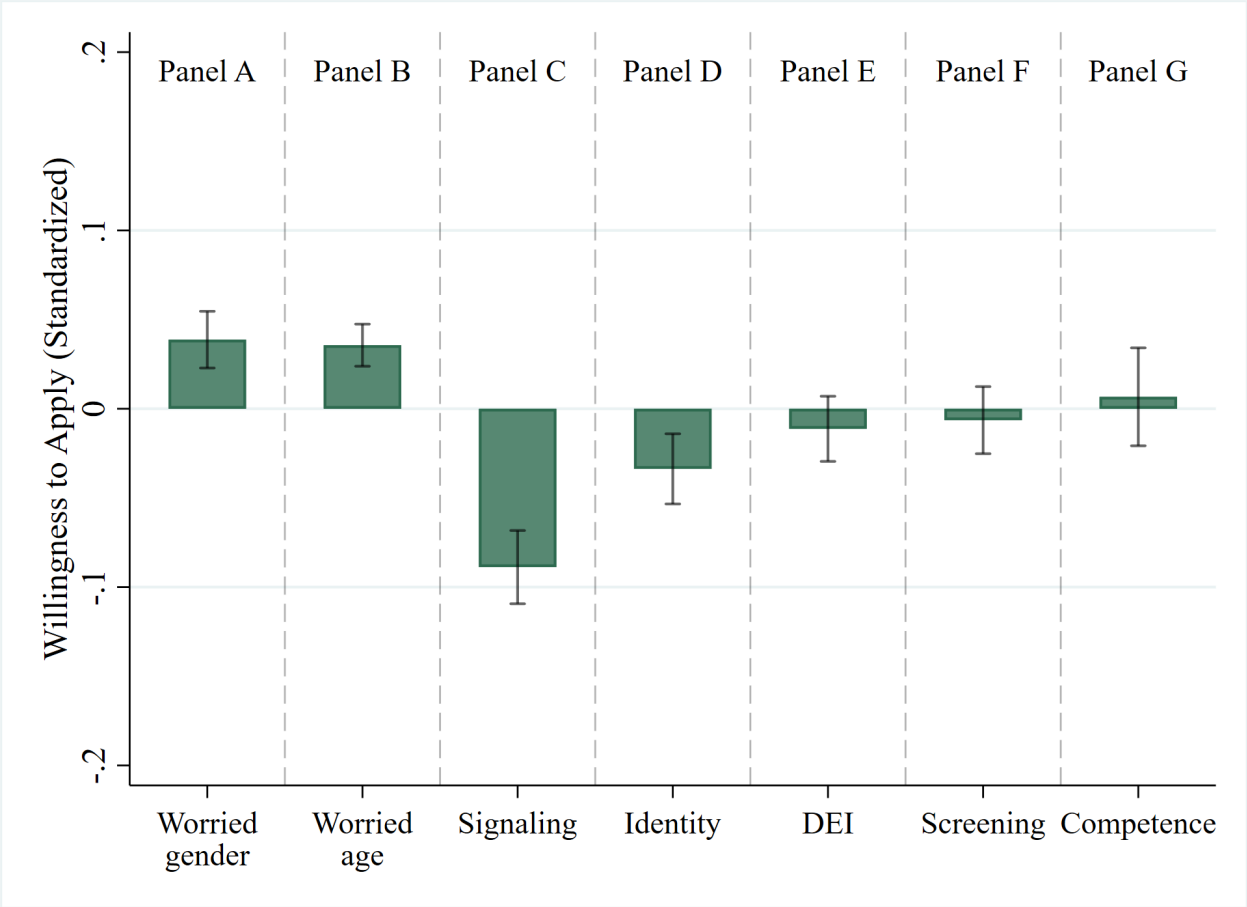
Notes: This figure shows coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. The dependent variable for the regression in Panel A is the answer to the following question: "How fair do you feel this rejection was?" (possible answers on a seven-point Likert scale, from "Completely unfair" (1) to "Completely fair" (7)). The dependent variable for regression results in Panel B 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). Whiskers mark 95% confidence intervals.

Figure A7. Candidates' Perception of Discrimination in the Broader Labor Market



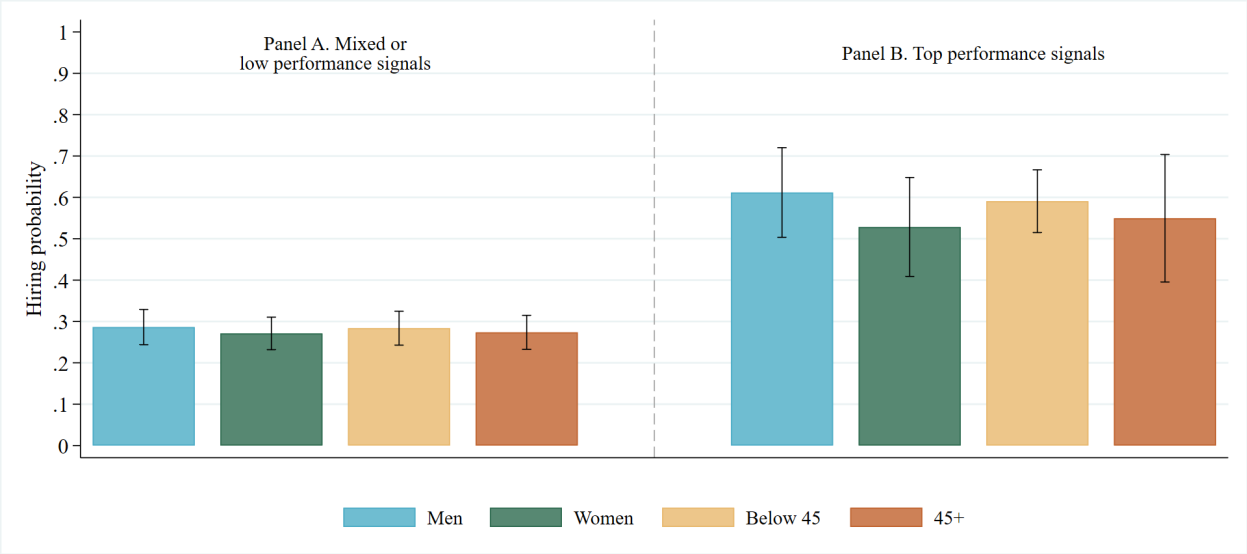
Notes: At the end of the survey, we asked candidates about their experiences of discrimination and their preferences regarding blind application processes in the labor market. This figure shows the share of respondents who answered that they were at least somewhat worried "about being discriminated against 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 A8. Candidates' Willingness to Apply Blind vs. Non-Blind: Mechanisms



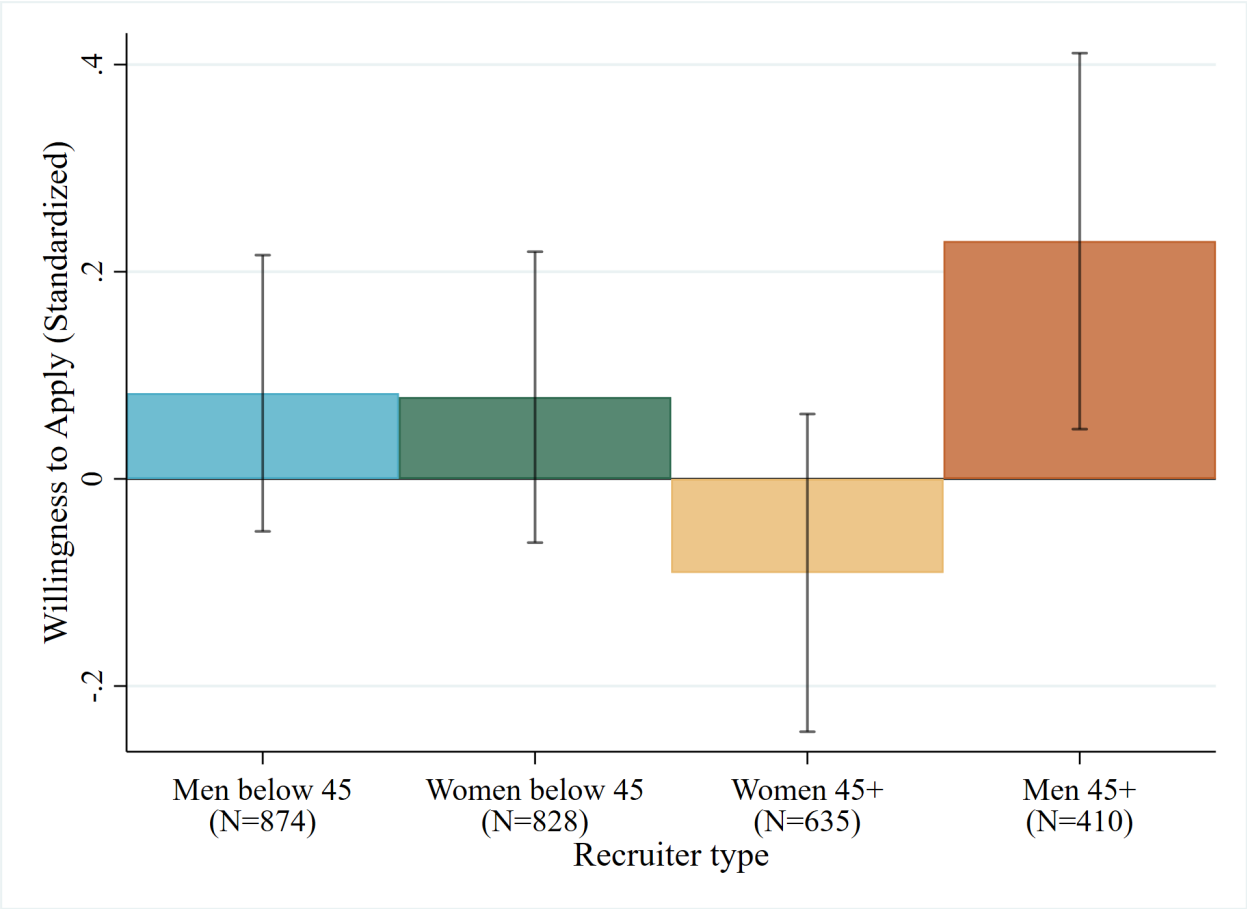
Note: Bars display coefficient estimates from seven separate OLS regressions in which the dependent variable is standardized candidate willingness to apply. The figure reports the coefficients on the interaction between Blind Applications (after rejection) and each variable shown. The variables are based 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 7 and Appendix A. All regressions include fixed effects for test scores, favorite subject, and level of education. Whiskers mark 95% confidence intervals.

Figure A9. 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 A10. 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.

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 1st Price List

Dependent variable:	WTA (standardized)	
	First list	Second list
Blind application	-0.03	0.04
	(0.07)	(0.07)
Women	-0.21***	-0.22***
	(0.06)	(0.06)
Age	-0.06	-0.13**
	(0.06)	(0.06)
Blind × Women	0.04	0.10
	(0.08)	(0.08)
Blind × Age 45+	-0.04	0.10
	(0.08)	(0.08)
Test score	0.08***	0.06***
	(0.01)	(0.01)
Favroite subject		
Social sciences	0.03	0.03
	(0.05)	(0.05)
STEM	0.28***	0.30***
	(0.05)	(0.05)
Educational attainment		
Bachelor's degree	0.26***	0.22***
	(0.04)	(0.04)
Advanced degree	0.23***	0.30***
	(0.06)	(0.06)
Observations	2,488	2,488
R^2	0.08	0.08

*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. Clustered standard errors at the candidate level are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table A5. OLS Predicting Initial Willingness to Apply: Controlling for Risk Preferences

Dependent variable:	Willingness to apply (standardized)			
	Non-blind application		Blind application	
	(1)	(2)	(3)	(4)
Women	-0.22***	-0.18***	-0.14***	-0.10**
	(0.04)	(0.04)	(0.04)	(0.04)
Age 45+	-0.10**	-0.09**	-0.06	-0.06
	(0.04)	(0.04)	(0.04)	(0.04)
Risk preferences		0.05***		0.05***
		(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	0.10	0.09	0.10

*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: *** $p<0.01$ and ** $p<0.05$.*

Table A6. Willingness to Apply Before and After Rejection

Dependent variable:	Willingness to apply (standardized)
	(1)
Blind application	-0.00
	(0.02)
Women below 45	-0.22***
	(0.06)
Men 45+	-0.09
	(0.06)
Women 45+	-0.31***
	(0.06)
Blind application × Women below 45	0.08***
	(0.03)
Blind application × Men 45+	0.04
	(0.03)
Blind application × Women 45+	0.09***
	(0.03)
Controls	
Test score	X
Favorite subject	X
Education	X
Observations	4,976
R-squared	0.08

*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. The regression includes controls for test scores, , and fixed effects for 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 A7. OLS Predicting Measures of Hiring Rates

Dependent variable:	Likelihood to be hired			Others: Non-blind			Others: Blind		
	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	-3.11***	-6.83***	0.50	-6.42***	-4.79***	-8.02***	9.59***	9.51***	9.77***
	(0.88)	(1.24)	(1.25)	(0.78)	(1.12)	(1.09)	(0.78)	(1.11)	(1.10)
Age 45+	-1.33	-2.56**	0.06	-2.26***	-1.24	-3.37***	4.19***	4.45***	3.86***
	(0.86)	(1.21)	(1.22)	(0.76)	(1.10)	(1.06)	(0.78)	(1.11)	(1.09)
Post-rejection	-6.53***	-6.81***	-6.28***	-1.54***	-1.43**	-1.64***	0.07	0.69	-0.58
	(0.70)	(0.98)	(0.98)	(0.43)	(0.61)	(0.59)	(0.48)	(0.69)	(0.68)
Women × Post-rejection	-2.10**	0.87	-4.88***	0.10	-0.69	0.84	-1.48***	-2.40***	-0.53
	(0.83)	(1.13)	(1.21)	(0.50)	(0.73)	(0.69)	(0.55)	(0.78)	(0.77)
Age 45+ × Post-rejection	-1.33	0.02	-2.62**	0.56	0.16	0.95	-0.84	-0.52	-1.15
	(0.84)	(1.13)	(1.22)	(0.50)	(0.73)	(0.69)	(0.55)	(0.78)	(0.77)
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	0.14	0.14	0.17	0.05	0.04	0.07	0.08	0.09	0.08

*Notes: Coefficient estimates from OLS regressions, which include fixed effects for test scores, favorite subject, and level of education. "Likelihood to be hired" (Columns (1) to (3)) 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). "Others: Non-blind" (Columns (4) to (6)) refers to candidates' answers to the following question: "What do you think is the overall percentage of candidates hired when resumes included age and gender?" (in percentage points). "Others: Blind" (Columns (7) to (9)) refers to candidates' answers to the following question: "What do you think is the overall percentage of candidates hired when resumes did NOT included age and gender?" (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 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 A9. 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	-0.09**	-0.09***	0.00	-0.16***
	(0.04)	(0.03)	(0.04)	(0.05)
Women	-0.22***	-0.29***	-0.18***	-0.40***
	(0.04)	(0.04)	(0.05)	(0.05)
Age 45+	-0.10**	-0.11***	-0.07	-0.16***
	(0.04)	(0.04)	(0.05)	(0.05)
Test score	0.06***	0.05***	0.05***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
Blind application × Women	0.08***	0.12***	0.11***	0.14***
	(0.02)	(0.02)	(0.03)	(0.03)
Blind application × Age 45+	0.03	0.08***	0.10***	0.06**
	(0.02)	(0.02)	(0.03)	(0.03)
Blind application × Test score	0.02***	0.02***	0.01	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Controls				
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 favorite subject and level of education. Clustered standard errors at the candidate level are in parentheses. Significance levels: *** p<0.01, ** p<0.05 and * p<0.1.*

Table A10. OLS Predicting Relative Benefit of Blinding

	Benefit of Blinding	
	(1)	(2)
Women	1.00***	0.93***
	(0.07)	(0.16)
Age 45+	0.55***	0.14
	(0.07)	(0.16)
Test score	0.08***	0.03
	(0.02)	(0.03)
Women × Test score		0.02
		(0.04)
Age 45+ × Test score		0.10***
		(0.03)
Controls		
Favorite subject	X	X
Education	X	X
Observations	2,488	2,488
R^2	0.11	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 and ** p<0.05.*

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 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 A13. Impact of Blind Applications on Willingness to Hire

Dependent variable:	Willingness to hire (standardized)				
	(1)	(2)	(3)	(4)	(5)
Blind	0.03	0.03	0.04	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 A14. 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 A15. 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	-0.06	-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			-0.20***	-0.21**	-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	1,702	1,045	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 A16. 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.

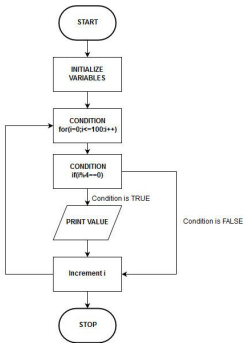
B Technical Test

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
2. What is this code an example of?

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

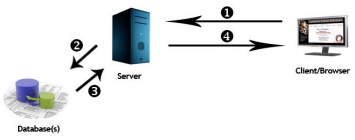
   A. **Executable Machine code**
   B. High-level programming code
   C. Assembly code
   D. Pascal programming code



3. 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?

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

   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 == 8 and level == 6, which will be the output?

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

   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 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.

C.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).

C.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.

C.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.

C.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.[43] 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.[44]

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*

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

[44] 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.

Supplementary material

A Experimental Design

A.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.

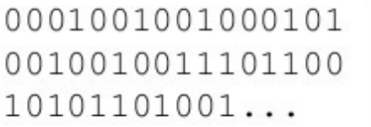
Below are the 10 questions. Candidates saw these questions in random order. The test had a time limit and used images to prevent online searching or copying.

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

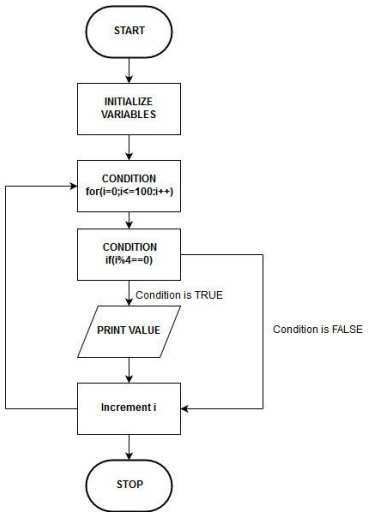


2. What is this code an example of?

   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?

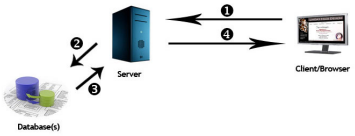
A. The value of z is x + y.
B. **The value of z is 11.**
C. x + y
D. 11

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 == 8 and level == 6, which will be the output?

   A. salary *= 1.05
   B. salary *= 1.04
   C. salary *= 7
   D. salary *= 1.06

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

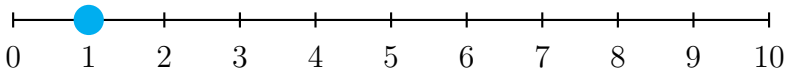
In addition to this information about the candidates, we also have samples of their performance on the technical test. For each candidate, the computer randomly chose two out of the 10 test questions. We can show you how the candidate did on these two questions. For instance:

Sample Performance on Technical Test

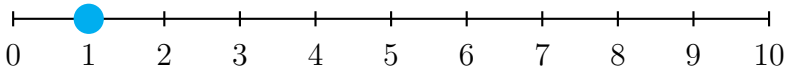
0 out of 2 correct	1 of 2 correct	2 of 2 correct

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

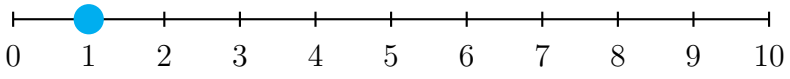
What do you think the average score on the technical test was for **men**?



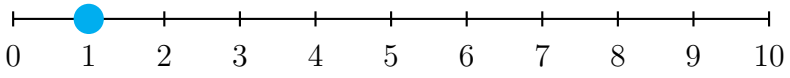
What do you think the average score on the technical test was for people **younger than 45**?



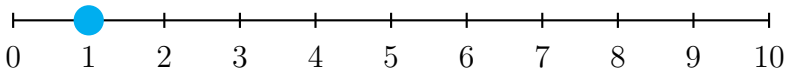
What do you think the average score on the technical test was for **people whose favorite subject is the humanities (such as writing, languages, art)**?



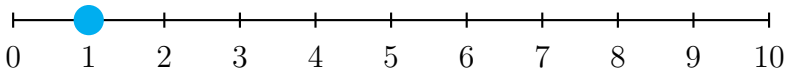
What do you think the average score on the technical test was for **people who have an advanced degree**?



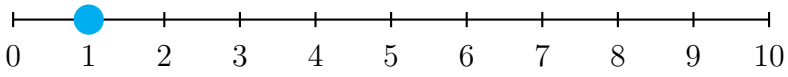
What do you think the average score on the technical test was for **people whose favorite subject is STEM (such as science, technology, engineering, or math)**?



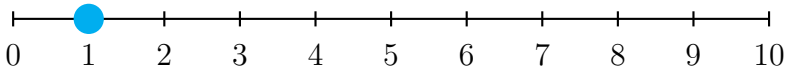
What do you think the average score on the technical test was for **women**?



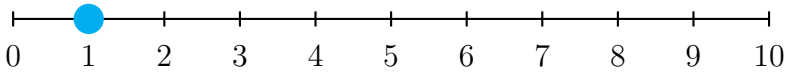
What do you think was the average test score for people **45 and older**?



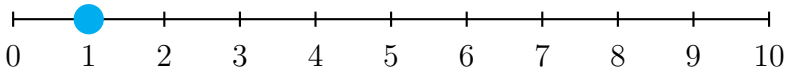
What do you think the average score on the technical test was for **people whose highest degree is a bachelor's degree**?



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)**?



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



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

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

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:

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.

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

- 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
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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.

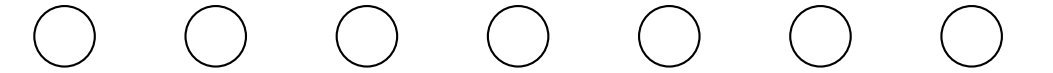
- ☐ High School Degree or Less
- ☐ Bachelor's Degree
- ☐ Advanced Degree

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

A.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?

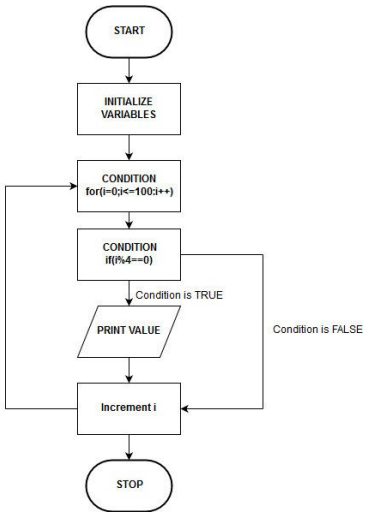
   A. **Executable Machine code**

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.

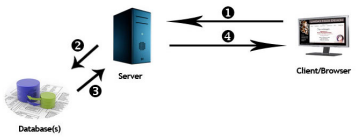
B. **The value of z is 11.**

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.

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.

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

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**

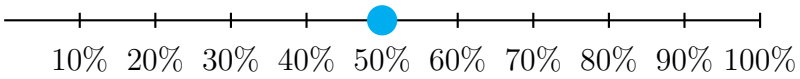
Now, you can decide whether you would want to apply with this resume by completing the list below.
If this question is the decision-that-counts for bonus, the computer will pick a random row and implement your choice for that row. In that case, if you choose to apply, you will be hired only if a randomly 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?

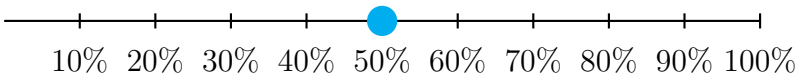
Much more likely when my resume **INCLUDES** age and gender	More likely when my resume **INCLUDES** age and gender	Somewhat more likely when my resume **INCLUDES** age and gender	No difference	Somewhat more likely when my resume does **NOT INCLUDE** age and gender	More likely when my resume does **NOT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

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



(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?

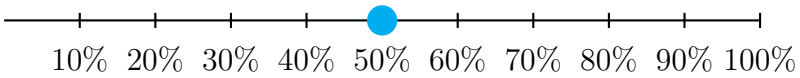


(The "next" arrow will work after you move the slider)

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?



(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.

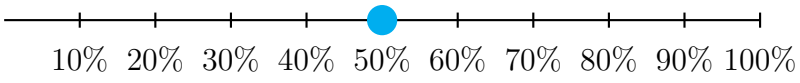
Recall that your resume displayed your performance on two random questions of the technical test. How many of these two questions do you think the recruiter saw you got right? If you guess correctly and this is the decision-that-counts for bonus, you'll get $1.

☐ 0 correct
☐ 1 correct
☐ 2 correct

How fair do you feel this rejection was?

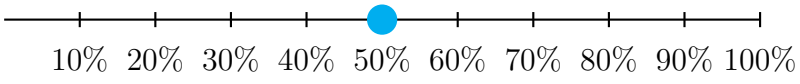
Completely unfair	Mostly unfair	Slightly unfair	Neither fair nor unfair	Slightly fair	Mostly fair	Completely fair
○	○	○	○	○	○	○

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



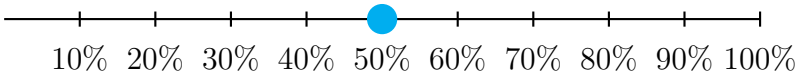
(The "next" arrow will work after you move the slider)

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



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

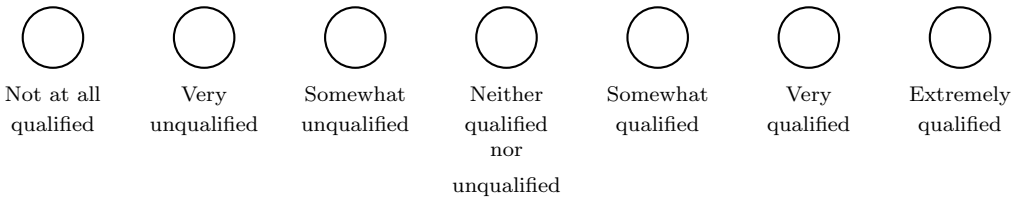
What do you think is the overall percentage of candidates hired when resumes **did NOT included** age and gender?



(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?

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



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**

Remember that this is what your resume 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	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

- 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.