Pre-Analysis Plan for
"The Effects and Dynamics of Blind Hiring"

By

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1 Introduction

Our study focuses on the impact and underlying mechanisms of blind hiring, a recruitment / candidate evaluation practice increasingly adopted to mitigate recruiter bias, enhance equity, and promote diversity in hiring. Although blind hiring can manifest in various forms across industries and cultural contexts, our research examines focus on the information technology (I.T.) industry in the United States, particularly in the recruitment of entry-level technical positions (i.e. software engineer). In this context, we define *blind hiring* as the blinding of observable group characteristics—specifically, gender and race/ethnicity—during candidate evaluation.

Beyond the impact of blinding, our study examines how biases or preferences differ between and propagate across hiring stages in a setting where multiple decision-makers, with potentially different goals and preferences, participate sequentially in candidate evaluation. Recruitment typically proceeds in two distinct phases: an initial application or résumé-based screening stage conducted by Human Resources (HR) personnel, followed by a technical evaluation stage conducted by engineers. While HR may emphasize firm-level objectives, including diversity and inclusiveness, engineers typically assess candidates who would join their own teams, thereby potentially placing greater weight on dimensions such as technical competence and team fit. These differing focal points may lead to systematic differences in evaluations between the two stages. In this setting, we aim to study the dynamics of multi-stage hiring and how it may interact with blind hiring.

2 Research Questions

We aim to answer the following primary questions under an experimental set-up:

1. Do agents in different stages of the hiring exhibit different hiring preferences (e.g., based on candidates' demographic characteristics)?
2. How does blinding the observable group characteristics affect employers' subjective evaluation of job applicants?

   (a) Does this, in turn, alter the composition of candidates who advance or are ultimately hired?

3. How does the effect of blind hiring interact with multiple stages of hiring?

3 Motivation / Literature

Blind hiring is increasingly adopted globally across various industries with the aim of reducing bias and discrimination, while promoting equitable opportunities and diversity in recruitment. Blind hiring can take different forms depending on industry-specific and cultural contexts. For example, in the music industry, blind hiring may involve blind auditions (Goldin and Rouse, 2000). In South Korea, it includes omitting college names, self-portrait pictures, and information on familial backgrounds, such as parents' occupations, from job applications, while in the U.S. and European countries, blind hiring often involves the omission of race/ethnicity and gender.

The existing literature on blind hiring generally supports the notion that blind hiring enhances the likelihood of minority candidates receiving callbacks and being invited to interviews.[1] For example, Goldin and Rouse (2000) find evidence of 'blind' auditions increasing the probability of women advancing and being hired in orchestras. Similarly, Åslund and Nordström Skans (2012) find that, in Sweden, anonymous job applications increase the chances of both women and non-Western origin immigrants advancing to the interview stage.

However, these outcomes appear to be *context-dependent* and the effectiveness of blind hiring can vary across different settings and stages of the hiring process (Rinne, 2018). Åslund and Nordström Skans (2012) also note that while women saw improved job offer rates under blind hiring, the benefits for ethnic minorities diminished once anonymity was removed in the subsequent interview stage. In France, Behaghel et al. (2015) find evidence that, when firms voluntarily select into blind hiring, participating firms may become less likely to interview and hire minorities. This may occur due to selection and because anonymization prevents the attenuation of negative signals when an application belongs to a minority or hinders affirmative action.

Literature on interventions for mitigating discrimination in the hiring process is sparse. Furthermore, many of the literature that studies blind hiring only focuses on blinding in the initial stage of the hiring process, and ignores that hiring process is often multi-stages involving multiple decision-makers. Our proposed research aims to contribute to a more nuanced understanding of blind hiring by investigating its

[1] See (Rinne, 2018) for a summary.

effects within two-stage hiring processes, as often done during recruiting in technical sectors.

4 Data and Experimental Design

Our research draws on two primary data collection exercises that simulate the hiring and candidate evaluation process:

(i) (Job applicant-side data) information on job seekers' resume, observable characteristics, and coding productivity measured through a survey and a coding test (see Section 4.1)

(ii) (Employer-side data) information on employers' characteristics and recruiting behavior, collected from a randomized control trial with firms actively seeking to hire college graduates in computer science or related fields (see Section 4.2).

4.1 Job applicant-side: Coding Evaluation and Survey with UC Berkeley CS Students

The proposed research involves examining the impact of blinded review of job applications (resumes) and/or programming code scripts on various hiring-related outcome variables. To do so, we first need to recruit prospective job seekers and collect their demographic information, resumes, and programming scripts from a controlled coding lab. UC Berkeley students students constitute the pool of *job applicants* in our experimental design. These materials are essential for the subsequent employer-side experiment, where participating firms will simulate actual recruitment process at an I.T. firm, evaluating candidates based on resumes and performance on coding tasks.

4.1.1 Job Applicant (Student) Sample Recruitment

Participants for the student-side survey and coding lab is recruited from 3rd and 4th-year Computer Science (CS) or Electrical Engineering and Computer Sciences (EECS) majors at the University of California, Berkeley (UCB), who are seeking employment. We recruit participants via an email invitation coordinated with the relevant department.

The students will be incentivized in three ways. First, they receive $20 upon participating in our study. In addition, students can earn an additional bonus of up to $20 based on their performance in the coding lab. Second, students have an opportunity to prepare for a coding interview task by participating in our experiment. Third, the resumes and codes of the participating students will (optionally) be sent to employers, participating in our employer-side experiment, who are actively looking to hire job candidates with CS/EECS degrees. Employers may contact students for a job application, which can lead to a job offer. Students are free to ignore employers' emails if they are not interested.

4.1.2 Coding Task and Survey

Coding tasks is administered in person at the Xlab in UC Berkeley. Each student is provided with a computer to complete two coding questions – one easy and one more difficult –using an online coding interface hosted on a professional assessment platform.[2,3] To ensure the integrity of the exercise. lab computers is set-up with security features (i.e. Firefox Kiosk mode and key blockers) that prevent access to external resources such as ChatGPT. All sessions are proctored. Participants may code in C++, Python, or Java.[4]

In addition to completing the two tasks, students submit their latest resumes and answer survey questions on basic demographics and perceived discrimination in the I.T. industry. Collected resumes are reformatted to create a uniformly formatted set of resumes for use in the subsequent firm-side experiment (see Section 4.4). Submitted codes will be anonymously graded by two professionals with substantial industry experience. The grading criteria are as follows:

- Accuracy – whether the compiled code passes pre-specified test cases (25% of overall grade).
- Readability and design – subjectively evaluated by the two graders (50% of the overall grade, with each grader contributing 25%).
- Efficiency – measured by run and compile time within each language (25% of the overall grade, relative to other codes with the same language).

4.2 Employer-side: Firm Experiment and Surveys

4.2.1 Sample and Recruitment

We recruit employer participants working in the U.S. I.T. industry who are actively involved in hiring entry-level software engineers for full-time or internship positions.

[2] The questions are designed with input from experienced tech workers.

[3] Remote Interview IO is one of the platforms commonly used by the I.T. industry to conduct technical screening and live coding interviews,

[4] These are the most commonly used languages among UC Berkeley computer science students.

To mirror real-world hiring practices, our employer-side experiment enrolls two types of decision-maker: Human Resources (HR) professionals, who are typically responsible for resume screening, and software engineers, who further evaluate technical ability. While the real-world hiring process often unfolds sequentially, our design collects evaluations from both groups concurrently to isolate stage-specific preferences and combine the results to mimic a two stage hiring process.[5]

For the first stage (i.e., resume screening stage), we will recruit 100+ Human Resources (HR) personnel via mass email.[6] In the email invitation described in Figure 1, employers are informed that they will be asked to rate formatted resumes created from those of CS students, and that upon completion of the survey, they will receive original resumes of CS students based on their preferences indicated in the survey.[7]

Figure 1: Recruitment Message for Firm Participants

Academic Study on Hiring in Tech — Paid 10–15-Minute Survey Inbox ×

Seung Yong Sung (UC Berkeley) <csjobresearch@berkeley.edu> 11:15 AM (0 minutes ago)
to me

Dear HR Officer / (Name),

We are a research team at UC Berkeley and the University of Michigan studying how companies recruit early-career CS graduates. We'd love your perspective as someone involved in hiring. In a short survey (10~15 minutes), we will ask about your insights on how candidates are evaluated and review a few student candidates "applications". In return, you'll receive:

- A **$25 gift card** for completing the survey
- (Optional) **Additional $10 gift card** for each colleague you invite from your firm who completes the survey.
- Entries into a **lottery for six $50 gift cards**.
- (Optional) A **personalized list of upcoming graduates from UC Berkeley with degrees in Computer Science** vetted via our in-person coding tests and matched to your preferences, whom you can consider for hire or for referral

Why this matters
Your input helps us understand how hiring decisions are made—and could shape future recruiting practices. You'll also gain early access to qualified CS grads, complete with résumés, objective code scores (graded by industry professionals), and unassisted coding samples.

Follow this link to the Survey: Take the survey

For questions, reach out anytime at csjobresearch@berkeley.edu.

Thank you for your time, and we look forward to your insights!

Sincerely,

[PI Name], on behalf of the research team

** This program is approved by the University of Michigan and University of California Institutional Review Boards.*
*** Your email was obtained via an online platform (Apollo.io) that allows users to find targeted industry contacts.*

Follow the link to opt out of future emails: Click here to unsubscribe

For the second stage, we recruit 100+ software engineers who will be asked to conduct further technical evaluation of candidates. The second-stage participants will be

[5] A typical hiring process in the I.T. industry includes at least two stages: the first stage is a resume-screening stage in which HR professionals review applicants' resume and determine which applicants advance; and the second stage is a technical coding interview stage in which senior engineers assess coding and technical skills through online or in-person coding tasks.

[6] Industry contacts are collected via app.Apollo.io.

[7] To prevent any discriminatory consequences from reaching our students, we will not incorporate protected class variables, such as race or gender, into our algorithm for matching firms to actual resumes or student.

recruited through the same email invitation channel.

Participants are also asked to invite colleagues (HR or Engineers in their own firms).

4.2.2 Incentives

Employer participants are incentivized in several ways. First, participants receive monetary incentives upon completion; HR participants receive $25, and engineer participants receive $40. Second, participants are enrolled in a lottery with six winners that provides $50 with higher chances of winning if they more correctly guess the student's actual coding ability, as measured by student's performance during the coding task described in section 4.1. Third, participants are asked at the end of the survey whether they would like to receive resumes, codes, and the contact information of matched students. This is motivated by the Incentivized Resume Rating (IRR) methodology, as outlined in Kessler et al. (2019). Participants are also paid $10 per successful invitation of their coworkers into the survey.

4.2.3 Stage 1: Baseline Employer Survey for HR professionals

The first stage of the employer-side experiment resembles the *resume-screening* stage of a hiring process, where employers conduct an initial screening based on information revealed in the resumes and decide whether to pass the resume to a subsequent technical interview stage. The survey consists of several modules, including the randomization stage.

Module 1. Consent and Screening: Baseline employer (HR) survey begins with consent and screening questions. The screening criteria are built as follows:

1. Employers who consent to participate in the study
2. Employers who have not participated in the study before.
3. Employers whose employment status is full-time or part-time employees.
4. Employers who reside and work in the U.S.
5. Employers who are aged 18 or over.
6. Employers who consider themselves tech industry workers.
7. Employers who consider themselves HR professionals.
8. Employers who have experience hiring for technical positions.

Employers who do not satisfy the above conditions are screened out.

Module 2. Demographic Questions: We collect information on their demographic characteristics, firm characteristics, and information on the position the company is hiring for.

Module 3. Randomization and Candidate Evaluation : Firm participants are randomized into control and treatment groups. Participants assigned to the treatment group receive resumes with applicants' names blinded, while participants in the control group receive the same set of resumes, but the names of the applicants will be revealed. Note that the names on the resumes are not real student names, but hypothetical names, which are randomly assigned to each resume (see more details about resume creation in Section 4.4).

After being randomized, firm participants are asked to evaluate 18 student resumes across various dimensions:

1. How good do you think this person will be in *coding*? [scale from 1-10][8]
2. How good of a *fit* do you think this person will be in your workplace? [scale from 1-10]
3. How likely would this person *stay* in your company for the next 5 years? [scale from 1-10]
4. How would you rate this person *overall*? [score between 0 and 100]
5. Would you *select* this person *to advance* to the next hiring stage for more in-depth technical evaluation?

Module 4. Questions about Hiring Experience: We ask about participants' past hiring experiences, such as the type of hiring stages that they have been involved in or how long they have been involved in recruiting for technical positions. We ask questions about how their firms conduct the hiring process and what factors are important in assessing a job applicant's productivity.

Module 5. Questions about Current Hiring Policies: We collect information on the hiring policies of the firm where participants work and ask whether the firms implement any policies related to diversity, equity, and inclusion (DEI) during hiring process and their views on DEI policies.

Module 6. Invitation of co-workers and IRR: Finally, participants are asked to invite HR or engineer from the same firm.

Before exiting the survey, participants are asked whether they would like to be connected with UC Berkeley's CS students. If they say "yes", we email them real resumes

[8] Participants are incentivized to correctly guess the student's actual coding ability via a lottery.

and codes of students that correspond to their own preferences revealed in the survey, as in the IRR method.

4.2.4 Stage 2: Baseline Employer Survey for Software Engineers

The second stage with technical professionals resembles the *interview* stage of a job application, where employers gain more information about job applicants by having them complete specific coding tasks. All modules of the survey are identical to the HR professionals employer survey described in section 4.2.3, except module 3.

In module 3, technical professionals will see the same set of resumes for evaluation and follow the same randomization as HR personnel. In line with the technical evaluation engineering team usually conduct, they will additionally see *the codes of the applicants* collected from our coding task provided with details of the coding task and simple metrics on student performance (whether the code compiles, and *the accuracy score* described in 4.1.2).[9] Technical professionals will evaluate resumes for the same set of questions as the HR, except for the last question that asks the HR if the resumes should be passed to the interview stage.

4.2.5 Embedded On-Task Tracker

Both stages of the employer-side survey embed "TaskMaster" (Permut, 2019) in Qualtrics to record, for each page, *active time* and total elapsed time. This distinguishes time actually spent on the page from time when the survey tab is background.[10] Therefore, TaskMaster may provide better measure of time spent on evaluating each candidate and also provides indirect evidence of participants *potentially* consulting outside sources (i.e. Google / LinkedIn searches) that could undo our randomized and assigned demographic signal by revealing true underlying demographics. Note, in the survey, at the end of Module, we do ask firm participants directly whether they used outside sources and searched for the resume owners, while evaluating the candidates.

4.3 Follow-Up Survey

We will conduct a short follow-up employer survey within 6 months after our baseline survey for those who participated in our study and received students' resumes. The aim is to obtain the following information:

[9]We do not provide the full coding score graded by the industry professional that additionally comprises readability and design, and efficiency; See 4.1.2.

[10]Qualtrics reports total elapsed time for the survey page; TaskMaster can exclude off-tab intervals.

- Whether they reached out to any of the candidates we matched them with.
- Whether any candidate(s) proceeded to further stages (e.g., interview) or were eventually hired.
- The reasons behind not reaching out to candidates at all (if applicable).

This information will be utilized to assess the effectiveness of the experiment's incentives related to the IRR method and to determine the satisfaction of the firms with the recommendations provided.

4.4 Resume Creation and Name Selection

We will reformat the student resumes collected from the UCB CS students who participated in the coding task in order to control for non-quantifiable variations in resume designs and to focus on variation in quantity and quality of students' academic, leadership, and career-oriented (work and project) experiences. The reformatted resume closely resembles the actual resumes provided by the student participants - only occasional and minor changes are made in order to remove obvious gender and race/ethnicity signals from students' descriptions of experiences. For example, a description of extra-curricular activity organizing a club trip to Chicago for Chinese students would have the word "Chinese" removed, such that the gist of responsibility and accomplishment would not change, while allowing for the blinding to remain intact when this resume is evaluated by the firms assigned to the full and partial blinding treatment arms.

To create the names for the resumes, we followed the approach by Kessler et al. (2019). For first names, we select the most common names in California between 2000-2007 using data from the Social Security Administration. We only keep the first names that strongly signal gender, by keeping the first names that have more than 99% occurrence in one gender. We then used (Tzioumis, 2018) that reports the probability of race for each first names, and kept the names that had probability greater than 70% for each race.[11] We also removed any names that strongly signals religion, or had names that could be ambiguous in race/gender from outside-US context.[12] For the last names, we used the data from Census 2010 and kept all last names that has probability greater than 70% to belong to a specific race. We then took the most common last names within each race, and randomly matched the last names with the first names within

[11] For Asian first name, we used the same names as the White names, because there is no popular Asian first names. Race is signaled by last name for Asian.

[12] Christian and Jesus is removed for religious names, and names like Andrea which is feminine in US but masculine in other contexts are removed.

the same race to create the full names.[13]

4.5 Data Quality Checks

For the employer survey, although we believe that the incentives designed via the employer-employee matching will be sufficient for employers to report truthfully in the survey, we will include a question aimed at capturing respondents' attention within the survey. We will indicate:

1. Whether employers answered the attention question correctly.
2. Whether employers rank among the top 5% in terms of the fastest total time spent on the survey.
3. Whether employers paid attention to resume evaluation.[14]

We will define different samples based on these quality cutoffs and assess whether the quality of submissions is affected by our treatments. We will also collect employers' work email addresses to identify and eliminate duplicate survey responses.

4.6 Outcomes

The primary outcome variables measured via the survey are:

1. How good do you think this person will be in coding? [scale of 0 - 10]
2. How good of a fit do you think this person will be in your workplace? [scale of 0 - 10]
3. How likely would this person stay in your company for the next 5 years? [scale of 0 - 10]
4. How would you rate this person overall? [value between 0 and 100]
5. (HR participants only) Would you select this person to advance to the next hiring stage for more in-depth technical evaluation? [Yes/No]

[13] For Asian last names, we chose Chinese and Indian last names, because we are also interested in the differences in employers' evaluation of Chinese and Indian applications, two of the most common races in the tech industry.

[14] Examples of employers who did not pay attention include those who provided resume evaluations where there is no variation in ratings across all 24 resumes.

5 Empirical Analysis

In this section, we present a series of empirical analyses that we will conduct after collecting data from both student and employer experiments, in order to study the impacts and dynamics of sequential and blind hiring.

5.1 Preferences by Hiring Stages

To estimate the preferences of each stage (HR or Engineers) over race/gender of the job applicants, we run the following regression using only the data of candidate evaluations conducted by HR and Engineers under non-blinded conditions:

$$y_{i,s} = \alpha_0 + \beta_1 Race\_Gender_{i,s} + \mu_i + \omega_{i,s} + \delta_s + \varepsilon_{i,s}, \tag{1}$$

where $y_{i,s}$ is the evaluation score of resume i by respondent s (an individual HR professional or engineer) for the outcomes listed in Section 4.2. $Race\_Gender_{i,s}$ is a set of indicator for six demographic groups (one omitted category). μ_i denotes resume (content) fixed-effects; $\omega_{i,s}$ denotes position (resume-order) fixed effects; δ_s is respondent fixed effects.

In addition, we can check if the HR or the engineer has different preferences on race and gender by running the following regression:

$$\begin{multline} y_{i,s} = \alpha_0 + \beta_1 Race\_Gender_{i,s} + \beta_2 (Race\_Gender_{i,s} * Stage_s) + \\ + \mu_i + \omega_{i,s} + \delta_s + \varepsilon_{i,s}, \end{multline} \tag{2}$$

where $Stage_s$ equals 1 for Engineers and 0 for HR.

5.2 Effects of Blind Hiring by Hiring Stages

To estimate the treatment effect of blind hiring on the employers' subjective evaluation and how it varies by the race and gender indicated on the resume, we run the following regression:

$$y_{i,s} = \gamma_0 + \gamma_1 BH_s + \gamma_2 Race\_Gender_{i,s} + \gamma_3 BH_s \times Race\_Gender_{i,s} + \mu_i + \omega_{i,s} + \delta_s + \varepsilon_{i,s}, \tag{3}$$

where $y_{i,s}$ is the subjective evaluation of resume i by employer s; BH_s is the indicator that is equal to 1 if employer s received a blinded resume.

We can also study if blind hiring leads to employers making better inferences on the coding ability of the resumes by running the following regression:

$$Subjective\_Coding_{i,s} - Coding\_Score_i = \beta BH_s + \gamma Race\_Gender_{i,s} + \delta BH_s \times Race\_Gender_{i,s} + \mu_i + \omega_{i,s} + \delta_s + \varepsilon_{i,s} \quad (4)$$

To compare whether HR and engineers respond differently to the same resume due to the blind hiring, we can run the following regression:

$$y_{i,s} = \beta BH_s + \gamma Stage_s + \delta BH_s \times Stage_s + \mu_i + \omega_{i,s} + \theta_i + \varepsilon_{i,s}, \quad (5)$$

where θ_i is the resume fixed effects.

5.3 Two-Stage Dynamics of Blind Hiring

To study how the effect of blind hiring treatment perpetuates through a two-stage hiring process, we first construct a match between HR and engineers. Let $\mathcal{J}$ denote the ordered pair (h, e) of HR professional h and engineer e. When both HR and engineers receive the exact same resume, both in content and assigned name (race/gender signals), we match HR results with that of engineers (described in more details in section 4.4).[15]

Each pair $\mathcal{J}$ can be assigned into the following pair-specific treatment arm based on their respective individual treatment status:

1. *Control group*, where both HR and engineer receive non-blinded applications;
2. *Realistic blind hiring*, where only HR professional receives blinded applications, and engineer receives non-blinded applications;
3. *Complete blind hiring*, where both HR and engineer receive blinded applications.

We need to identify the job applicant that would be hired by the pair $\mathcal{J}$ in order to study the dynamic effects of blind hiring. Let $\mathcal{C}$ be the number of resumes that are passed from HR to the engineers. Because both HR and engineers are reviewing the same set of resumes, $\mathcal{C}$ is a variable that we can flexibly control. For a given $\mathcal{C}$, we rank the resumes that HR reviews according to their reported overall evaluation score, and select the top $\mathcal{C}$ resumes to be passed to the engineer. We then select the top resumes that the engineer evaluates according to their reported overall evaluation score among the $\mathcal{C}$ set of resumes that are passed by HR to the engineer. Let $i^{\mathcal{J}}$ denote the final candidate hired by the pair $\mathcal{J}$.

[15] This implies that each HR or engineer will appear in more than one pair in the pair-level regression.

5.3.1 Effects of Blind Hiring: Full Hiring Process

We can then run the following regression in order to study how blind hiring affects the productivity and the demographic composition of the hired candidate:

$$y_{\mathcal{J}} = \gamma_0 + \gamma_1 Realistic_{\mathcal{J}} + \gamma_2 Complete_{\mathcal{J}} + \varepsilon_{\mathcal{J}}, \tag{6}$$

where $y_{\mathcal{J}}$ is the actual coding score or the proportion of demographics of final hired candidate $i^{\mathcal{J}}$.

Note that the coefficient γ is a function of the number of resumes passed to the technical interview stage $\mathcal{C}$. We can then study how the treatment effect of blind hiring changes according to $\mathcal{C}$ by running the regression 6 with different $\mathcal{C}$.

5.4 Heterogeneity Effects of Blind Hiring

Due to the ex-post matching, we are able to control which HR is matched to which engineer. We can then study the treatment effect of blind hiring for specific cases:

1. When HR is pro-DEI and engineer is not pro-DEI (defined by above median level for each stage).
2. When HR is pro-DEI and engineer is pro-DEI
3. When HR is not pro-DEI and engineer is not pro-DEI
4. When HR is not pro-DEI and engineer is pro-DEI

We construct the DEI measure of the HR and engineer by creating a summary index across all DEI questions and standardizing the index. We then estimate regression 6 for each of the four cases above to understand when blind hiring is most (or least) effective.

In order to examine the heterogeneous treatment effects of blind hiring, we run the following regression:

$$y_{i,s} = \beta BH_s + \gamma D_s + \delta BH_s \times D_s + \gamma Z_i + \omega_i + \delta_s + \varepsilon_{i,s}, \tag{7}$$

where D_s refers to the employer respondent-level variables, such as:

- Whether the respondent holds high DEI preference
- Whether the respondent works in a big firm
- whether the respondent works in a diverse workplace
- whether the respondent is male

- whether the respondent is a race-minority

We also study the distributional effect of blind hiring over the actual coding scores of the students by running the Recentered Influence Functions (RIF) for the equation 6 where the outcome variable is the actual coding scores of the final hired candidate $i^{\mathcal{J}}$.

5.5 Multiple Hypothesis Testing

We will account for multiple hypothesis testing by controlling familywise error rate (FWER) as proposed by List et. al (2016). We plan to construct family by the level of analysis done:

- Ordered pair $\mathcal{J}$
- HR professional h
- Engineer e

5.6 Constructing Standard Errors

Because the level of randomization is done on the employer-level, all analysis will have standard errors clustered at the employer level (either h or t). For analysis done on the ordered pair (h, t) level, we will cluster the standard errors using two-way clustering by HR and engineer.

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