Taryn versus Taryn (she/her) versus Taryn (they/them): A Field Experiment on Pronoun Disclosure and Nonbinary Hiring Discrimination

Taryn Eames*

updated March 9, 2024

Abstract

Thousands of randomly generated, fictitious resumes were submitted to job postings in pairs where the treatment resume contained pronouns listed below the name and the control resume did not. Two treatments were considered: nonbinary "they/them" and binary "he/him" or "she/her" pronouns congruent with implied sex. As such, I estimate discrimination against nonbinary and presumed cisgender applicants who disclose pronouns. Results show that nonbinary applicants face discrimination: disclosing "they/them" pronouns reduces positive employer response by 5.4 percentage points. There is also evidence that discrimination is larger (approximately double) in Republican than Democratic geographies, potentially reflecting attitudinal differences. By comparison, results are inconclusive as to whether presumed cisgender applicants who disclose pronouns are discriminated against. Hence, it is not the act of pronoun disclosure that leads to discrimination against nonbinary applicants but the fact that those pronouns are "they/them."

JEL Codes: C93, J15, J16, J23, J71

*PhD Candidate, Department of Economics, University of Toronto, 150 St. George Street, Toronto, Ontario, Canada (email: taryn.eadie@mail.utoronto.ca; will be updated to taryn.eames@mail.utoronto.ca shortly). This study could not have been completed without tireless research assistance from Siu Lun Cheong, Hanru He, YuHui Li, Minh Thuy Phi, and Sarah Zahir. I am grateful to Philip Oreopoulos who helped me access the resources needed to complete this project. I thank Philip Oreopoulos and David Price for invaluable suggestions and feedback throughout the study. I also thank Peter Cziraki for a Research Fellowship associated with this study and Andràs Tilcsik for helpful advice. The pre-analysis plan and populated pre-analysis plan (following Duflo et al. 2020) for this experiment can be found on the American Economic Association Randomized Control Trial Registry (Trial #11183). Ethics approval was obtained from the University of Toronto Social Sciences, Humanities and Education Research Ethics Board (Human Research Protocol #44259).

Sharing pronouns is becoming increasingly common in social interactions, the workplace, and recently the job market. Job seekers now have the option to include pronouns on resumes and many are doing so. A 2022 Resume Builder survey finds that when asked about how often they review resumes with pronouns listed, 74% of hiring managers said 'somewhat' or 'very' often (Resume Builder 2022). However, pronoun disclosure carries additional identity signals and thus potentially opens applicants up to discrimination. This may be especially true when pronoun disclosure reveals a minoritized gender identity, as for nonbinary applicants. In this study, I investigate hiring discrimination against nonbinary applicants who disclose "they/them" pronouns; in doing so, discrimination against presumed cisgender applicants who disclose binary "he/him" or "she/her" pronouns is also investigated. By comparing discrimination faced by nonbinary and presumed cisgender applicants who disclose pronouns, discrimination against applicants who disclose "they/them" pronouns can be decomposed into the portion driven by the act of pronoun disclosure generally and by the applicant's nonbinary gender identity. I leverage a resume audit study design with pronoun disclosure as the treatment of interest.

To motivate this research, first consider that nonbinary gender identities are becoming more common, especially among younger generations. A 2022 Pew Research Center survey finds that while only 0.1% of those 50 or older identify as nonbinary, this is true for 3.0% of those 18 to 29 (Brown 2022). The Williams Institute find a similar trend, estimating that 1.2 million adults identify as nonbinary in the U.S. and 76% of them are 18 to 29 (Wilson and Meyer 2021). Understanding how nonbinary people are treated in the labor market is thus becoming increasingly important as this group grows in size and as nonbinary youth age into the labor force. Second, nonbinary people experience relatively poor labor market outcomes. Research consistently shows that transgender people (some of whom identify as nonbinary) have lower employment rates, lower incomes, and higher poverty rates compared to cisgender people (Leppel 2016, 2021; Carpenter et al. 2020, 2022). Further, Shannon (2022) finds that genderqueer and nonbinary identifying people have lower incomes compared to transgender men and women and notes that this is "consistent with [gender nonconforming and nonbinary people] facing additional income penalties from identifying outside of the more socially accepted male/female binary." In addition, nonbinary people report facing significant intolerance and discrimination. From the 2015 U.S. Transgender Survey (which includes nonbinary respondents), 30% of respondents report being fired, denied a promotion, or otherwise mistreated in the workplace in the last year (James et al. 2016). This provides suggestive evidence for discrimination as a potential driver of worse economic outcomes for nonbinary people.

Inspired by Bertrand and Mullainathan (2004), correspondence studies have become a common experimental method used to causally estimate discrimination. Beginning with race, these field experiments have been used to investigate discrimination against a host of marginalized groups in multiple contexts (Baert 2018 provides a review). Most relevant to this study are correspondence studies focused on hiring discrimination against the LGBT community, and gender-diverse populations in particular. Granberg et al. (2020) use an unmatched correspondence study to investigate hiring discrimination against transgender men and women in Sweden. They find that transgender applicants are 6 percentage points less likely to receive a positive employer response than presumed cisgender applicants; estimates are only robust to the Heckman-Siegelman critique when comparing transgender applicants to the dominant gender in male- or female-dominated occupations.[1] Considering pronoun disclosure, Kline et al. (2022) conduct a massive resume correspondence study involving 83,000 applications to entry-level jobs at 108 Fortune 500 companies across the U.S. (each employer was sent thousands of resumes). While they focus primarily on racism and sexism at the per-employer level, a small subset of resumes include pronouns listed below the applicant's name. They find that gender-typical (binary) pronouns are associated with a contact penalty of 1.3 percentage points with marginal statistical significance; gender-neutral (nonbinary) pronouns are associated with a penalty of 1.7 percentage points and also marginally significant.[2] Finally, Business.com conduct a non-academic unmatched correspondence study evaluating hiring discrimination against nonbinary applicants (McGonagill 2023). Here, two identical resumes are generated for the same fictitious applicant, where the only difference is that one has "they/them" pronouns listed below the gender-ambiguous name and the other does not. In total, applications are sent to 180 remote, entry-level business positions requiring an undergraduate degree. McGonagill finds that the control applicant received 9 percent more interest from employers.

This study contributes to existing research as the first large-scale study focused on investigating hiring discrimination against applicants who disclose pronouns. From May to October 2023, 7,970 resumes were submitted in pairs to job postings in 15 occupations across six U.S. cities. Compared to Kline et al. (2022), this experiment considers a wide range of employers rather than focusing on very large companies only. This matters due to, among other things, the proliferation of Application Tracking Systems (ATS) and heterogeneous use among companies of different sizes. While 99% of Fortune 500 companies use ATS, this is true for

[1]Heckman and Siegelman (1993) and Heckman (1998) present a critique of audit studies which shows that if there is a difference in the variance of unobserved productivity determinants between groups, this can result in biased estimates of discrimination. This is discussed in more detail in Section 3.5.

[2]Gender-typical pronoun estimates are statistically significant at the 10% level in the full sample but statistically insignificant in the balanced sample. Gender-neutral pronoun estimates are statistically insignificant in the full sample but statistically significant at the 5% level in the balanced sample.

66% of large companies and only 35% of small organizations (Myers 2023). Importantly, a core functionality of these systems is to parse resumes, organize extracted data into a standardized format, and store in a central database for hiring managers to peruse (FindErnest 2023). This may not matter for identity signals communicated through name (race, sex) but it does matter for identity signals communicated via pronoun disclosure on a resume PDF. Unless the hiring manager opens an applicant's formatted resume (rather than relying on extracted data organized via ATS), the identity signal is not being communicated and no discrimination can occur. As a result, the external validity of Kline et al. (2022) may be limited to very large companies and not reflective of hiring discrimination more generally.

Compared to McGonagill (2023) this study is large-scale, resumes are randomly generated (versus identical except for treatment assignment), and I explore multiple occupations (versus focusing on entry-level business positions only). Together, this increases external validity, power, and precision; reduces template bias; and enables the exploration of additional hypotheses. Further, this study leverages two distinct treatments: nonbinary pronouns ("they/them," signaling the applicant is nonbinary and disclosing pronouns) and binary pronouns congruent with sex implied by name ("he/him" or "she/her," signaling the applicant is cisgender and disclosing pronouns).

The inclusion of two treatments is a key contribution of this paper: it enables the decomposition of discrimination faced by applicants who disclose "they/them" pronouns into the portion driven by the act of pronoun disclosure (which presumed cisgender applicants who disclose pronouns also face) and by applicants' nonbinary gender identity. This is important because, in recent years, pronoun disclosure has become divisive. Sentiment is split along political lines: a 2022 YouGov poll finds that, when asked to think about information people put on social media profiles, email signatures, or when introducing themselves 40% of Republicans but only 10% of Democrats believe that "people should generally not say / display their pronouns unless asked" (Ballard 2022). As a result, pronoun disclosure carries political signals that are communicated regardless of implied gender identity. This is especially pertinent since there is evidence that minority political signals can induce hiring discrimination (Gift and Gift (2015)). It is also possible that some employers view resumes as an inappropriate place to disclose pronouns, view the practice as unprofessional, or infer other information about applicants who choose to list pronouns on their resume (regardless of gender identity–for example, maybe these applicants are "woke").

This study is focused on two primary research questions. Do applicants who disclose nonbinary "they/them" pronouns during the hiring process experience discrimination? If so, to what extent can this be explained by the act of pronoun disclosure generally versus identity-based discrimination specific to nonbinary applicants? In other words, is it the fact that pronouns are being disclosed at all that leads to discrimination, or is it the fact that those pronouns are "they/them"? This can be achieved by comparing positive employer response rates for applicants who disclose nonbinary pronouns to response rates for presumed cisgender applicants who disclose binary pronouns. Secondary hypotheses, informed by existing research and described below, are also explored. These hypotheses consider whether discrimination magnitude varies based on applicant, geographic, occupation, and job posting characteristics.

First, I consider whether discrimination differs geographically along political lines. This is motivated by evidence that discrimination against LGBT people varies geographically, and that acceptance of transgender identities is partisan. Denier (2017) found that sexual orientation wage gaps in Canada vary by geography and are largest in non-metropolitan areas. In the U.S., Tilcsik (2011) found between-state heterogeneity in discrimination faced by openly gay men which appears to reflect local attitudes and antidiscrimination laws (although it is unclear which is driving outcomes). This study builds on Tilcsik's findings by considering within-state heterogeneity in political partisanship. By controlling for state-level similarities, this study focuses on attitudinal differences between Democratic and Republican geographies. This is intuitive: evidence suggests that, in addition to pronoun disclosure, acceptance of nonbinary people is politically divided. In a 2022 Pew Research Center survey, 66% of Republicans but only 10% of Democrats say that "society has gone too far in accepting transgender people" (Parker et al. 2022); a 2022 YouGov poll shows that 66% of Republicans but only 37% of Democrats are somewhat or very uncomfortable using gender-neutral pronouns (Ballard 2022).

I also investigate whether discrimination differs between nonbinary applicants with male-sounding names and those with female-sounding names. This is motivated by evidence that, within the LGBT community, people assigned male at birth tend to experience worse labor market outcomes than those assigned female. Research consistently shows that while gay men experience a wage gap compared to similar heterosexual peers, lesbian women experience a wage premium (Black et al. 2003; Antecol et al. 2008; Drydakis 2012; Nauze 2015; Waite et al. 2019; Drydakis 2021; Jepsen and Jepsen 2022). In a meta-analysis of hiring discrimination against gay men and lesbian women, Flage (2019) shows that there is consistent evidence of discrimination against both groups, but discrimination is larger on average against gay men. Considering transgender people, longitudinal studies have shown that transgender women's earnings significantly decrease post-transition while the earnings of transgender men remain unchanged or slightly increase (Schilt and Wiswall 2008; Geijtenbeek and Plug 2018).

Following Becker (1957), I also consider whether employers may be discriminating on behalf of their customers by comparing occupations with higher and lower levels of customer interaction (as in Granberg et al. 2020). If discrimination is higher in occupations requiring more customer interaction, this suggests employers may be discriminating based on customer taste. Considering another occupational difference, I investigate whether discrimination is heightened in male- or female-dominated occupations. This is motivated by Granberg et al. (2020), who found robust evidence of discrimination against transgender men and women in male-dominated and female-dominated occupations only. Finally, I contextualize estimates by comparing results to another group that experiences discrimination: females in male-dominated occupations (and vice-versa; Rich 2014; Yavorsky 2019; Cortina et al. 2021).

I find that on average, disclosing "they/them" pronouns reduces positive employer response by 5.4 percentage points compared not disclosing pronouns. Compared to presumed cisgender applicants who disclose binary "he/him" or "she/her" pronouns, positive employer response is reduced by 3.7 percentage points. Hence, an estimated 67% of discrimination against applicants disclosing "they/them" pronouns is due to their nonbinary gender identity. Finally, there is evidence that discrimination is higher in Republican geographies and that applicants with multiple minoritized identities are doubly disadvantaged. By comparison, results are inconclusive for presumed cisgender applicants who disclose pronouns: while there is evidence against positive discrimination, it is unclear whether these applicants are experience no discrimination or some negative discrimination.

This paper is structured as follows. In Section 1, I describe the audit study design: how resumes are constructed, geography and occupation selection, and the process used to collect data. In Section 2, empirical strategy is described. In Section 3, I present results: summary statistics, regression estimates, intersectionality, and robustness checks. Finally, Section 4 discusses and concludes.

1 Audit Study Design

1.1 Resume Construction

1.1.1 Randomization Process

A process for generating occupation-specific resumes was developed using a program by Lahey and Beasley (2009). The characteristics over which resumes were randomized are equivalent across geographies, with the following exceptions: in Work Experience, company names are city-specific (position titles and descriptions are independent of geography); in Education, school names are city-specific (probabilities, degrees, and concentrations are independent of geography); in Certifications, names of licenses or other certifications may vary by geography if needed (e.g., the license required to serve alcohol differs by state). For all occupations and geographies, fictitious resumes were generated for an applicant born in 1999 (i.e., applicants are 24 in 2023); this is signaled by high school graduation year. Note that to facilitate the Neumark (2012) method to respond to the Heckman-Siegelman critique, variation in resume quality is required. This is achieved through randomization, especially randomized education and work experience.

Resumes are generated in pairs: within a characteristic, resumes can be "matched same" (i.e., if the first resume is randomly assigned characteristic A, then the matched pair will also be given characteristic A) or "matched different" (i.e., if the first resume is randomly assigned characteristic A, then the matched pair will be randomly assigned a characteristic aside from A). To limit fraud detection by email providers and job boards, there were in total two female names and two male names used in each state (i.e., all matched resume pairs in Colorado where the name-implied sex is female will use the same two names). Emails were specific to names, and each name always used the same phone number, resume format, and application order when applying in a given city.

Within an occupation and implied sex, resumes are randomized across:

- Pronouns (Section 1.1.2): resumes are assigned one of nonbinary "they/them" pronouns, binary "he/him" or "she/her" pronouns congruent with implied sex, or no pronouns. Because I am most interested in identifying discrimination against applicants who disclose "they/them" pronouns, conditional on disclosure resumes have a two-thirds chance of being assigned nonbinary and one-third chance binary pronouns. Pronouns are matched different: exactly one resume in each pair has no pronouns.

- Summary (Section 1.1.3): resumes are assigned a summary, selected without replacement from a list of 12 inputs, where four are occupation-specific summaries and eight are no summary. Resumes are matched different: no two resumes will have the same summary (though they can both have no summary).

- Education Level (Section 1.1.4): resumes are assigned an education level where probabilities are occupation-specific and informed by observed prevalence. Resumes are matched same in terms of the highest level of education received: conditional on having a high school diploma, applicants' high schools are nearby and have similar academic performance. Resumes are matched different in terms of high school name and post-secondary concentration (if applicable).

- Work Experience, 2015-2017 (Section 1.1.5): in the last two years of high school, applicants were assigned one of two work experiences (or no work experience). Experience is selected without replacement from a list of seven inputs, where five are no experience.

Resumes are matched different: no two applicants can have the same work experience (though they can both have no work experience during this period).

- Work Experience, 2017-present (Section 1.1.5): after high school, applicants are assigned four work experiences. Experiences are selected without replacement from 43 possible position and description pairs. Resumes are matched same in terms of whether the applicant's last job is in the job posting occupation and years of experience in the job posting occupation. Resumes are matched different in terms of job titles, company names, and position descriptions.

- Skills Listed: each applicant has six skills listed. Skills are randomly selected without replacement from a list of 18 skills; three are selected from nine occupation-specific skills, the others are selected from nine skills that are independent of occupation. Resumes are matched different: applicants will never have the same skill listed.

Resumes are also assigned a name (Section 1.1.6) which additionally determines the phone number, resume format (Section 1.1.7), and order applications are sent in. Names are randomly assigned and independent from the above.

1.1.2 Pronoun Treatments

Pronoun disclosure is the treatment evaluated in this study. In the first treatment group, applicants list nonbinary "they/them" pronouns under their name and are thus signaled to be nonbinary and disclosing pronouns. Hence, treated applicants are open about their nonbinary gender identity and comfortable enough in that identity to list pronouns on their resume. As such, these applicants may be different from other nonbinary applicants who are less open about their gender identity. This is a common limitation in studies that estimate discrimination against the LGBT community where identity is typically signaled through implicit or explicit disclosure (Flage 2019; Granberg et al. 2020). Though it is not addressed here, it is worth considering to what extent nonbinary applicants who list "they/them" pronouns on their resume are the same or different from those who do not.

In the second treatment group, applicants disclose binary "he/him" or "she/her" pronouns congruent with name-implied sex and are thus signaled to be cisgender and disclosing pronouns. Through this paper, I refer to these applicants as "presumed cisgender" and disclosing pronouns. While there is no guarantee employers will interpret binary pronoun disclosure this way, it is a reasonable expectation. First, LGBT groups have encouraged pronoun disclosure among cisgender people in the workplace as an inclusive act (GLAAD 2021; Gelpi et al. 2020). This idea has also been shared in mainstream publications: for example, the New York Times published an editorial supporting the inclusion of pronouns in workplace email signatures among cisgender workers (Galanes 2021). Considering pronoun disclosure on resumes specifically, resume advice websites typically mention that listing pronouns on a resume is a step towards inclusivity for cisgender applicants (Kohler 2021; Mahtani 2022; Rorris-Crow 2022). Similarly, disclosing pronouns in social media profiles has been encouraged among cisgender people as inclusive. For example, after Instagram added this feature, transgender athlete Schuyler Bailar quickly shared a photo to the platform of him holding a sign that reads "Put your pronouns in your bio! (Especially if you're NOT trans!)" alongside information on how to make the update (Bailar 2021). In terms of how common the practice is, Tucker and Jones (2023) found that among U.S. users, in the first six months of 2022, 4.6% of Twitter bios had pronouns listed; of these, just over 80% were either "he/him" or "she/her."

1.1.3 Summary

A "summary" is a brief, typically one-sentence objective or summary statement that may be included at the top of a resume. An example of a summary input for applicants applying as an administrative assistant is "To secure a position with a well-established organization with a stable environment that will lead to a lasting relationship." Summaries are occupation-specific, and each occupation randomizes across four summary inputs (or no summary). The majority (67%) of resumes do not contain a summary–see Section 1.1.1 for information on the randomization process.

Occupation-specific summaries were sourced from resumes of job seekers on the same large job board website used to apply to job postings, for workers living in Idaho who currently hold that occupation. A state outside the geographies included in the study was selected to ensure that the fictitious resumes used in this experiment were not submitted alongside resumes from which resume attributes were sourced. Idaho was chosen specifically because it is adjacent to all three states of interest (Washington, Utah, and Colorado). Ordering resumes by date of upload to the job board website, summary inputs were taken from the first four resumes which included a summary or objective statement. In some cases, summaries were deemed inappropriate and disregarded (e.g., if the applicant discussed their intention to make a career change or where the summary could not be made generalizable across resumes that would be randomized) or adjusted (to ensure generalizability).

1.1.4 Education

For each occupation, the percentage of applicants whose highest education level is GED, high school diploma, Associate's degree, and Bachelor's degree was identified by averaging resume data available on the large job board across the six geographies in this study. These percentages determine the occupation-specific probability of resume pairs being randomly assigned each education level. Applicants with a high school diploma received that degree in 2017, a GED in 2019, an Associate's degree between 2019 and 2022, and a Bachelor's degree in 2021 or 2022.

For resumes assigned a high school diploma, three pairs of high schools were identified for each city. Each pair includes two nearby public high schools (within 4 miles of each other) with similar academic ratings according to Niche (2023): an organization that tracks comprehensive data on schools across the United States. Conditional on being assigned a high school diploma, resumes are equally likely to be assigned a pair of schools with high, medium, or low academic performance (i.e., a Niche academic rating of "A," "B," or "C" and below respectively). Resumes are "matched same" in terms of high school quality: if the first applicant is randomly assigned to have attended a high academic performance school, the second applicant will be assigned the other high school in that pair.

For resumes assigned post-secondary education, schools and concentrations are occupation-specific. For each geography and occupation, education background information was scraped from the large job board for workers currently holding the occupation of interest: 20 who had an Associate's degree and 20 who had a Bachelor's degree.[3] In total, 2,510 observations were collected, where each observation includes the school name and concentration. From this data, the most common four degree concentrations were identified for applicants with Associate's and Bachelor's degrees held by workers in each occupation. In addition, the two most common schools these degrees come from (for each of the six geographies) were identified. Concentrations and schools are then used as occupation and geography-specific education inputs.

1.1.5 Work Experience

One challenge of randomizing work experience in the context of this study is that applicants are applying in various cities in relatively low-skill occupations. Given that low-skill workers tend to have lower geographic mobility (Schmutz et al. 2021), the experiment is designed such that fictitious applicants are all local to the city they are applying within. This must

[3]In cases where there did not exist 20 resumes of people currently holding that occupation in the geography of interest with one of these degrees, all available data was scraped

be reflected in their work experience; hence, company names must be geography-specific. Because applicants are "matched different" in terms of the companies they work at, sourcing entire work experience sections from actual resumes becomes infeasible: this may require finding a very large number of a particular type of company (e.g., construction companies) in each city. Finding so many company names, ensuring alignment between company names and job descriptions, and verifying the existence of the company during the claimed period of employment make this approach prohibitively difficult.

To overcome this, I leveraged an approach similar to Neumark et al. (2019) and sourced a pool of 188 job titles and descriptions from actual resumes scraped from the large job board website. From this collective pool, each occupation draws from an occupation-specific set of 43 work experience options, which are randomly combined to create a work experience for each fictitious applicant. For each occupation, 10 of the 43 potential entries are in the occupation of interest (i.e., for janitor applications, 10 of the 43 potential entries are in the janitor occupation). As described above, pairs of resumes are matched in terms of whether their last entry is in the occupation of interest and in terms of how many total years of experience in the occupation of interest position each resume has. Resume pairs have a 25% chance of having their last work experience entry in the occupation of interest; they have an approximately 43% chance of having one of their first three entries in the occupation of interest. Variation in the extent of relevant work experience helps distinguish between statistical and taste-based discrimination and allows for Neumark (2012)'s method to address the Heckman-Siegelman critique.

To identify the occupation-specific set of 33 work experience inputs outside of the occupation of interest, data was scraped from the resumes of real job seekers on the large job board website. For each geography and occupation, resume data was scraped from 150 resumes of applicants currently holding that occupation[4]. In total, 11,705 observations were collected, where each observation includes the last three positions listed on the resume. Using this data, for each occupation the most common 12 positions held by workers before getting a job in the occupation of interest were identified. These 12 positions make up the total set of 33 inputs, where their relative frequency is designed to be representative (reflecting how likely it is that someone in the occupation of interest previously held another position). Pooling the 43 work experience options across all 15 occupations, and re-using positions and job descriptions where possible, generates the total set of 188 work experience options.

For each of the 188 work experience options, job descriptions were taken from actual

[4] In cases where there did not exist 150 resumes of people currently holding that occupation in the geography of interest, all available data was scraped

resumes for workers living in Idaho who currently hold that position.[5] Ordering resumes by date of upload to the job board website, job descriptions were taken from the first resumes which included job descriptions listed in point form (or that could be easily converted into point form). As much as possible, descriptions were kept as-is (e.g., typos and grammatical errors were retained), but were adjusted or skipped as needed (e.g., if descriptions were too specific to the company of employment). While job descriptions were not city-specific, company names were. They were sourced from the list of most common companies worked at by job seekers who currently hold a position in that occupation and city. For some occupations, additional companies were found as needed. Companies were carefully selected to align with the job descriptions. For example, for a construction worker job description mentioning excavation, a company that appeared to offer excavation services was chosen. Similarly, for a receptionist role involving dental records, a company providing dental services was selected.

1.1.6 Names

The first names used in this study, where some imply the applicant is male and others female, are provided in Table 1. These names were randomly chosen among a list of 42 names that met two criteria. First, they were in the list of top 200 popular names given to babies born in the 1990s from U.S. Social Security (2023). Second, name-associated Warmth and Competence scores from Newman et al. (2018) were both between 1.95 and 3.25 (a range representing non-extreme scores).

The last names used in this study are provided in Table 2. These names were randomly selected from a list of 59 last names which met two criteria. First, they are in the top 100 most common last names in the United States from U.S. Census Bureau (2021). Second, the percentage of the population with the last name that are white is less than 80 and the percentage of the population with the last name that are African American, Pacific Islander, Native, or Hispanic is less than 40 (each, not combined; this data was also sourced from U.S. Census Bureau 2021). Overall, these last names are largely white but not strongly so: rather than being a strong indicator of race, last names were chosen to be racially ambiguous. As such, they are flexible to the racial norms of the geography and occupation: if in one geography, an occupation is dominated by a particular race, applicants would not be strongly signaled as differing from that norm.

[5] A location outside the geographies included in the study was selected to ensure that the fictitious resumes used in this experiment were not submitted alongside resumes from which resume attributes were sourced. Idaho was chosen specifically because it is adjacent to all three states of interest (Washington, Utah, and Colorado).

First names were randomly matched to last names, yielding the final list of 12 names used in this study. This final list of full names and emails, in addition to the states these applicants "live" in and the order in which they apply for jobs, is provided in Table 3. Note that 10 U.S. phone numbers were obtained for this study–two for each local area code (206 in Seattle, WA; 509 in Spokane, WA; 720 in Denver, CO; 719 in Colorado Springs, CO; and 801 in both Salt Lake City, UT and Provo, UT).

Note that to consider differences in discrimination magnitude by implied sex, I assume employers use applicant first names to infer sex (this assumption is not required for any other analyses). While this is obvious for applicants who do not disclose pronouns, it is less clear for applicants who disclose "they/them" pronouns. There is some evidence for this: from the 2015 U.S. Transgender Survey, while 61% of adult binary transgender men and women have changed their name on their driver's license, this is true for only 39% of nonbinary adults James et al. (2016). This is consistent with Pollitt et al. (2021) who find that transgender youth with a nonbinary gender expression are less likely to have a chosen name. Further, transgender and nonbinary people who change names typically do so to align their gender expression with their gender identity (National Center for Transgender Equality 2016); for nonbinary people, that likely means choosing a gender-neutral name. Hence, it is reasonable to expect that a nonbinary person with a gendered name was likely given that name (and thus, it signals sex assigned at birth).

1.1.7 Resume Formatting

Two resume formats are leveraged, which are designed to look as different from each other as possible (different font, different ordering of resume categories, different style, etc.). Once generated, resumes are adjusted as needed (by changing font size or margin width) to ensure they are always exactly one page long. An example of a matched pair of formatted resumes is provided in Figure 1 and Figure 2.

1.2 Geography Selection

Core Based Statistical Areas (CBSAs) chosen as geographies of interest within which to distribute fictitious resumes are provided in Table 4. Geographies were selected to include pairs of CBSAs that met three criteria. First, to impose consistency in discrimination legislation, CBSAs are located in areas that have explicit state-level legislation prohibiting labor market discrimination on the basis of both gender identity and sexual orientation.[6] Second, to ensure there would be a sufficient number of job postings in all geographies, CBSAs must have a population of at least 500 thousand. Finally, CBSA pairs must be in the same state and one must be categorized as Democratic and the other Republican. In all, this design prioritizes consistency in macroeconomic environments as well as state policy and legislation, to focus on attitudinal differences between Democratic and Republican regions.

An implication of focusing on states that have legislation prohibiting labor market discrimination on the basis of gender identity and sexual orientation is that hiring discrimination against nonbinary applicants in these states may be lower on average than in states that do not have this legislation. While these laws have generally been shown not to improve outcomes for transgender and nonbinary people (Leppel 2021; Carpenter et al. 2020), the kinds of states that select into them may be less discriminatory against these groups on average. As a result, discrimination estimates found here may represent a lower bound.

1.3 Occupation Selection

Fictitious resumes were sent in response to job postings in the occupations detailed in Table 5. Occupations were chosen to balance across worker composition and customer interaction categories, prioritizing those with high worker counts and job postings that did not require post-secondary education. Worker composition categories include female-dominated, non-dominated, and male-dominated occupations; categorization is based on the percentage of workers who are male versus female. If two-thirds or more of the workers in an occupation are male, the occupation is deemed male-dominated (vice-versa for female-dominated occupations). Customer interaction categories include high, medium, and low customer facing; categorization is based on Occupational Information Network (O*NET) scores representing the importance of "performing for people or working directly with the public. This includes serving customers in restaurants and stores, and receiving clients or guests" (National Center for O*NET Development 2023). Occupations with scores above 75 are deemed high customer facing, between 50 and 75 medium, and below 50 low. There are very few male-dominated occupations with high customer interaction, hence there are no occupations included that fit this description.

The 15 occupations included in this study are in general lower skill, requiring no more than a high school education. This influences external validity and was done for a few

[6]Note in *Bostock vs Clayton County, Georgia* the U.S. Supreme Court ruled that employment discrimination on the basis of sexual orientation or gender identity is illegal federally across all states (Minkin and Brown nd). However, some states additionally explicitly prohibit employment discrimination on this basis within their own state statutes (Movement Advancement Project 2023).

reasons. First, this study seeks to compare discrimination across occupations which vary in worker composition and degree of customer interaction. This requires applying across a multitude of occupations which is less feasible in higher-skill occupations where there are more barriers to application (e.g., specialized job boards and more communication among employers). Second, this study seeks to compare discrimination across geographies which vary politically; for each occupation, there must be sufficient job postings in all geographies. Again, this is less feasible with higher-skill occupations which tend to be more geographically concentrated (e.g., there are limited computer programming job postings in Spokane). Third, the majority of U.S. workers do not have post-secondary education: 62.1% have below a Bachelor's degree and 51.6% have below an Associate's degree (U.S. Census Bureau 2022a). Understanding discrimination in the context of these occupations is thus important.

This study covers a significant segment of lower-skill occupations, representing 15.1% of U.S. workers (U.S. Census Bureau 2022b). Hence, results are reflective of discrimination experienced in a wide set of lower-skill occupations and can likely be generalized across other similar occupations. However, its applicability to higher-skill occupations is limited due to potential differences in diversity objectives and hiring practices.

1.4 Data Collection Process

With a team of Research Assistants (RAs), between May and October 2023, 7,970 resumes were sent as matched pairs in response to 3,985 job postings on a large job board website. Every week, each RA was assigned a fictitious applicant and would apply to jobs on that applicant's behalf. They were given a weekly list of targets, where targets were generated to balance application counts across occupation, sex, and geography. Within 12 and 36 hours of the first application, the matched resume was sent to the same job posting by the second fictitious applicant.

When finding eligible job postings, RAs searched for jobs in Salt Lake City, UT; Provo, UT; Denver, CO; Colorado Springs, CO; Seattle, WA; and Spokane, WA. Jobs had to be posted within three days of the application date, had to be located within 25 miles of the city being searched, and had to be located in the correct state (this only applied to Spokane, which is near the Washington-Idaho border). RAs read each job posting to ensure the job being applied for was being categorized as the correct occupation, that it did not require more than one year of occupation-specific work experience, that it did not require other specific qualifications that were generally not incorporated into our resumes, and that it was not a supervisor or managerial role. A process was set up which enabled RAs to check whether we had already applied to a job posting under the same company name in the same state; if so, the job posting was rendered ineligible. An exception was made in cases where the first paired application occurred at least 3 weeks before the potential second paired application, the job posting is for a distinctly different occupation (e.g., applicants originally applied as a janitor and there is a new job posting for a receptionist), and the first and second paired applications are of different implied sexes. A second exception was made in cases where applications were sent to unique franchisees operating under one company name. These exceptions make up well under 1% of observations. In addition, a process was set up which enabled RAs to check the company name against a list of hundreds of job agencies; if the job was posted by a job agency, the job posting was rendered ineligible. Job agencies typically respond positively to all applicants since they seek to match a wide range of applicants with employers (regardless of skill or background experience)–hence, these "employers" make poor experimental targets.

Finally, some jobs require applicants to answer questions during the application process. As long as answers could be found directly in the resume (e.g., "what is your highest education level?" or "how many years of janitorial experience do you have?") RAs answered the question. If answers could not be found in the resume (e.g., "how would you describe your teamwork style?" or "why are you interested in this job?") answers would be left blank; if answers were required, this rendered the job posting ineligible. If jobs required that the applicant include a detailed work history (i.e., effectively having the applicant duplicate their resume in an alternative form), this also rendered the job posting ineligible. In this case, employers would be unlikely to open the applicant's resume and instead rely on the duplicate resume provided in the application; hence, no pronoun signal is being communicated. Finally, if job postings did not require that applicants attach a resume as part of the application process, this rendered the job posting ineligible. If no resume is required, it is unlikely that employers will open and review applicant's resumes.

The count of paired resumes sent to job postings in each occupation by treatment type and city is provided in Table 6 and Table 7. These tables show that application counts are generally balanced within CBSA, occupation, and treatment; there is also balance when aggregating across occupation categories. In total 1,304 pairs of resumes were sent to female-dominated, 1,376 to male-dominated, and 1,376 to non-dominated occupations; 1,176 resumes were sent to high, 1,623 to low, and 1,186 to medium customer facing occupations.

Employer responses (via voicemail, text message, email, and job board direct message) were carefully tracked and categorized, where positive employer response is the outcome of interest. As stated in the pre-analysis plan, "employer response [is] viewed as 'positive' if they contact the applicant and either offer an interview or request the applicant contact them" (Eames 2023). This excludes responses that are overtly negative, confirm application submission, invite applicants to fill out an additional application on another portal, and questions like "Are you still interested in the position?" which may be sent to all applicants. An alternative definition is also investigated: employer response is viewed as "positive" if there is any possibility that the response could be interpreted positively. Compared to the former definition, this alternative considers responses like "are you still interested in the position?" to be positive. It also considers cases where the employer asks the applicant to answer additional questions or take an online assessment to be positive.

2 Empirical Strategy

A pre-analysis plan for this study is registered on the American Economic Association Randomized Control Trial Registry (Trial #11183; Eames 2023). Following Duflo et al. (2020) an associated populated pre-analysis plan (where that plan is rigorously followed and all discussed analyses are presented) is available in Trial #11183 documents (Eames 2023) and in Online Appendix A. The empirical strategy employed here is very similar, and despite small methodology tweaks,[7] results are nearly identical.

To estimate discrimination against applicants who disclose nonbinary or binary pronouns, the following logistic regression is run:

(1) $$p_{ij} = \left(1 + \exp\left(\alpha + \gamma NB_i + \lambda B_i + X_i'\beta_1 + Z_j'\beta_2 + \varepsilon_{ij}\right)\right)^{-1}$$

where p_{ij} is the probability that applicant i will receive a positive response from job posting j, NB_i is an indicator variable which equals 1 if the resume has nonbinary "they/them" pronouns listed, B_i is an indicator variable which equals 1 if the resume has binary "he/him" or "she/her" pronouns listed, X_i is a vector of resume characteristics that may influence baseline employer response, Z_j is a vector of firm and job posting characteristics which many influence baseline employer response, and ε_{ij} is an error term. Standard errors are clustered at the job posting level and multiple specifications are run, where some include and some exclude (X_i, Z_j). Resume characteristics in vector X_i are described in Table 8; job posting and firm characteristics in vector Z_j are described in Table 9. Estimates $\hat{\gamma}, \hat{\lambda}$ can be interpreted as discrimination against applicants who disclose pronouns.

To determine the extent to which discrimination against applicants who disclose "they/them" pronouns is rooted in gender identity, the following logistic regression is run excluding control observations:

(2) $$p_{ij} = \left(1 + \exp\left(\alpha + \delta NB_i + X_i'\beta_1 + Z_j'\beta_2 + \varepsilon_{ij}\right)\right)^{-1}$$

Since all applicants disclose pronouns in this regression, δ represents the additional discrimi-

[7] For example, I cluster standard errors at the job posting level in this study versus the firm level in the populated pre-analysis plan.

nation nonbinary applicants face because the pronouns they disclose are "they/them" rather than sex-congruent "he/him" or "she/her."

Defining ξ as the proportion of discrimination faced by applicants who disclose "they/them" pronouns attributable to their nonbinary gender identity, this can be estimated:

$$(3) \quad \xi = \frac{\delta}{\gamma}$$

The remaining discrimination can be attributed to the act of pronoun disclosure (independent of which pronouns are disclosed; presumed cisgender applicants also face this discrimination).

To investigate secondary hypotheses (regarding how discrimination magnitude varies across applicant, geographic, and occupation characteristics) I run the following regression:

$$(4) \quad p_{ij} = \left(1 + \exp\left(\alpha + \gamma_1 NB_i + \gamma_2[NB_i \cdot I] + \lambda_1 B_i + \lambda_2[B_i \cdot I] + X_i'\beta_1 + Z_j'\beta_2 + \varepsilon_{ij}\right)\right)^{-1}$$

where I is a vector of interaction variables. Indicator interaction variables are described in Table 10. Where possible, a second version of regression (4) is investigated which replaces indicator variables with continuous variables described in Table 11.

Finally, to compare discrimination estimates driven by pronoun disclosure to another discriminated group (females in male-dominated occupations and vice-versa), and to consider intersectionality, I run the following logistic regression:

$$(5) \quad p_{ij} = \left(1 + \exp\left(\alpha + \gamma NB_i + \lambda B_i + \eta_1 M_i + \eta_2[M_i \cdot FD_j] + \eta_3[F_i \cdot MD_j] + X_i'\beta_1 + Z_j'\beta_2 + \varepsilon_{ij}\right)\right)^{-1}$$

where M_i is an indicator variable that equals 1 if the applicant is implied male (through name), F_i is an indicator variable that equals 1 if the applicant is implied female, FD_j equals 1 if the job posting is in a female-dominated occupation, and MD_j equals 1 if the job posting is in a male-dominated occupation.

3 Results

3.1 Summary Statistics

Figure 3 shows positive employer response rates by pronoun disclosure group. Table 12 shows the raw differences in positive response rates by pronoun disclosure, both in total and by group of interest (implied sex, geographic politics, occupation categorization). For each difference in response between treatment and control groups, Chi-squared test results are also reported. Table 13 shows the same information by geography (by state and by city); Table 14 by individual occupation.

From these tables come a few highlights. The raw reduction in response rate associated with pronoun disclosure is larger, and statistical significance is stronger, when "they/them" pronouns are disclosed than when "he/him" or "she/her" pronouns are disclosed by presumed cisgender applicants for almost every group. While differences in reduction magnitude across states appear negligible, differences between cities are larger and appear to be in line with political affiliation. Comparing outcomes across individual occupations, baseline positive employer response rates vary significantly (ranging from 16.1% to 47.5% for applicants who do not disclose pronouns). Unsurprisingly, when looking at occupations individually, the statistical significance of response reduction is limited due to small sample sizes.

3.2 Primary Hypotheses

Panel A of Table 15 reports regression results for equation (1). Note that discrimination estimates are very similar across regression specifications (unsurprising given that resumes are randomly generated). The preferred specification is (D) which includes both resume and firm controls, and shows that on average disclosing nonbinary "they/them" pronouns changes the rate of positive employer response by -5.4 percentage points relative to no pronoun disclosure. This estimate is statistically significant at the 0.1% level and the 95% confidence interval is 3.8 to 7.1 percentage points. By comparison, estimates for presumed cisgender applicants who disclose binary pronouns are statistically insignificant, with a 95% confidence interval of +0.6 to -3.9 percentage points. Hence, while I can effectively rule out positive discrimination, results are inconclusive regarding whether these applicants experience no discrimination or some negative discrimination.

Panel B of Table 15 reports regression results for equation (2), and shows that there is a statistically significant difference in discrimination between applicants who disclose nonbinary "they/them" pronouns and presumed cisgender applicants who disclose pronouns. Nonbinary pronoun disclosure changes the rate of positive employer response by an estimated -3.7 percentage points compared to binary pronoun disclosure; this estimate is statistically significant at the 5% level with a confidence interval of -0.8 to -6.6 percentage points. Combining Panels A and B, from equation (3) it can be estimated that 67% of discrimination faced by applicants who disclose "they/them" pronouns is gender identity-based; the remainder may be driven by the act of pronoun disclosure.

3.3 Secondary Hypotheses

Table 16 reports the results of equation (4) including Republican interactions only. From this table, discrimination against applicants disclosing "they/them" pronouns is estimated to be 3.5 percentage points at baseline (i.e., in Democratic geographies). In Republican geographies, discrimination increases by an estimated 4.0 percentage points (to 7.5 percentage points)–more than doubling. Results are robust to replacing the Republican indicator variable (which equals 1 when job postings are in Spokane, WA; Colorado Springs, CO; or

Provo, UT) with a Republican vote share variable (in linear and quadratic form)–though statistical significance is marginal in some cases. By comparison, there are no statistically significant differences in discrimination faced by presumed cisgender applicants who disclose pronouns–unsurprising given limited power.

Hence, discrimination against applicants disclosing "they/them" pronouns is higher in Republican than Democratic geographies. This may be driven by attitudinal differences: by focusing within-state, I attempt to control for macroeconomic factors and state legislation. Further, two of the three geographic pairs are neighboring, increasing their environmental similarities. However, it may not be: perhaps geographic politics are correlated with other factors that are leading to differences in discrimination. To illustrate this, Table 17 reports differences in county-level averages across a range of variables between Republican and Democratic CBSAs. In large Democratic CBSAs, county-level population density, median household income, and education level are higher compared to large Republican CBSAs; percent white and number of religious congregations per 100K are smaller. These trends hold for the geographies in this study's research sample.

Table 18 reports the results of equation (4) including all interactions. In terms of Republican interactions, results are consistent with Table 16. In terms of other investigated interactions, results are generally inconclusive. Unsurprising given limited power, I am unable to conclude whether implied sex or occupation characteristics are associated with discrimination magnitude (either positively or negatively).

3.4 Other Minoritized Identities

After finding evidence of discrimination against applicants who disclose pronouns, it is of interest to compare discrimination magnitude to other forms of discrimination and to consider applicants with multiple minoritized identities. Do applicants who disclose "they/them" pronouns experience more, less, or similar rates of discrimination compared to other marginalized groups? How do applicants with multiple minoritized identities fare? This can be done using the data collected for this study, by comparing positive employer response rates for applicants implied male versus female in occupations with different male-female worker compositions. Research consistently shows evidence of hiring discrimination against male applicants in female-dominated occupations and vice-versa for female applicants (Rich 2014; Yavorsky 2019; Cortina et al. 2021), making this insightful.

Table 19 reports results from equation (5) and shows that applicants who are implied male (through name) experience discrimination in female-dominated and non-dominated occupations. Positive employer response rates are an estimated 4.7 percentage points lower for males compared to females in these occupations. Applicants who are implied to be female experience discrimination in male-dominated occupations: positive employer response rates are 6.2 percentage points lower for females compared to males in these occupations. Hence, discrimination against applicants disclosing nonbinary "they/them" pronouns is of a similar magnitude to discrimination faced by males applying in female-dominated and non-dominated occupations and females applying in male-dominated occupations. However, whereas sex-based discrimination appears to be occupation-dependent, discrimination against nonbinary applicants appears to be cross-occupation.

Further, there is evidence that applicants with multiple moniritized identities are doubly disadvantaged: implied female applicants who apply in male-dominated occupations and disclose "they/them" pronouns face positive employer response rates that are an estimated 11.6 percentage points lower (10.1 for males in female-dominated or non-dominated occupations). This can be seen visually in Figure 5.

3.5 Robustness Checks

I conduct a variety of robustness checks, with detailed descriptions and results available in Appendix B.

First, I address the Heckman-Siegelman critique[8] using the Neumark (2012) method. I referenced Neumark et al. (2016) code to produce my results, switching their heteroskedastic probit model for a heteroskedastic logistic model. This approach requires an additional identifying assumption (some applicant characteristics affect perceived productivity and their impact does not vary between groups) with testable implications. Results are available in Table 20. From this table, there is no strong evidence that testable implications are violated (especially for nonbinary applicants). For applicants who disclose "they/them" pronouns, unbiased discrimination estimates remain statistically significant at the 5% level. For presumed cisgender applicants who disclose binary pronouns, unbiased statistical discrimination remains statistically insignificant.

Second, I produce Tables 15 to 19 but using a linear probability model in place of a logistic model–results are close to identical. I also produce Tables 15 to 20 where I use two alternative definitions of positive employer response. One of these alternatives is more strict about what is considered 'positive:' only interview requests are categorized as such. The second is less strict: any response that could be considered positive is categorized as such. Results across all three definitions are very similar.

[8]Heckman and Siegelman (1993) and Heckman (1998) present a critique of audit studies which shows that if there is a difference in the variance of unobserved productivity determinants between groups, this can result in biased estimates of discrimination.

To test for statistical discrimination, I interact years of relevant work experience with pronoun disclosure (following Granberg et al. 2020). Ostensibly, employers are forced to rely on statistical averages in lieu of candidate-level information. If an applicant has more years of relevant work experience, this increases the information employers have about applicants (and thus reduces the extent to which they must rely on statistics). Results are inconclusive regarding the extent to which work experience influences employer response.

4 Discussion and Conclusion

In this paper, I present the results of the first large-scale correspondence study focused on evaluating hiring discrimination based on pronoun disclosure. Two resume treatments were evaluated: nonbinary "they/them" pronouns and binary "he/him" or "she/her" pronouns congruent with implied sex listed below the name. To estimate discrimination, positive employer response rates for treatment resumes were compared to matched control resumes that did not list pronouns. To estimate the portion of discrimination faced by applicants who disclose "they/them" pronouns rooted in their nonbinary gender identity, positive employer response rates are compared to applicants who disclose binary pronouns.

Overall, there is strong evidence of discrimination against applicants who disclose nonbinary "they/them" pronouns: doing so was found to reduce positive employer response by 5.4 percentage points. Comparing applicants who disclose "they/them" pronouns to presumed cisgender applicants who disclose "he/him" or "she/her" pronouns, the former experience an additional 3.7 percentage point reduction in positive employer response. Hence, for applicants disclosing "they/them" pronouns, an estimated 67% of discrimination is estimated to be rooted in their nonbinary gender identity rather than the act of pronoun disclosure more generally. Note that these estimates may reflect a lower bound since all states in the study have explicit state-level legislation prohibiting labor market discrimination on the basis of gender identity and sexual orientation. By comparison, whether discrimination exists against presumed cisgender applicants who disclose pronouns is inconclusive. I can generally rule out positive discrimination, but am unable to determine if these applicants face no discrimination or some negative discrimination (95% confidence interval is +0.6 to -3.9 percentage points).

These results are notably different from Kline et al. (2022), who find that disclosing "they/them" pronouns reduces positive employer response by only 1.7 percentage points with limited statistical significance.[9] Not only does their point estimate fall outside the

[9] This is the balanced sample estimate which is statistically significant at the 5% level. In the full sample, the point estimate shifts to only -1.0 percentage points is statistically insignificant.

95% confidence interval found here (-7.1 to -3.8 percentage points), but the lower bound of their confidence interval does too (at -3.4 percentage points). This suggests that there may be important differences in hiring practices between very large Fortune 500 companies and smaller companies (differences could also be rooted in occupations and geographies). One potential driver may be the use of ATS: 99% of Fortune 500 companies use ATS.

Considering how discrimination varies geographically, I find that discrimination against applicants who disclose “they/them” pronouns is more than double in Republican than in Democratic geographies. These findings build on research by Tilcsik (2011) who finds that estimates of discrimination against openly gay men in the U.S. vary across states based on differences in political sentiment, policy and legislation, or both. This study controls for state-level economic environments, policy, and legislation by including pairs of Republican and Democratic geographies located in the same state. As such, differences in geographic politics may be driven by attitudinal differences. That being said, it may also or instead be driven by factors like population density, median income, or racial makeup which are correlated with geographic politics. For all other secondary hypotheses, discrimination results are inconclusive–generally unsurprising given limited power.

While I find inconclusive evidence on whether statistical discrimination exists (see Section 3.5), I argue that taste-based discrimination is a much more likely source. Consider that the vast majority of Americans do not know anyone who uses gender-neutral pronouns: from a 2021 Pew Research study, 74% of Americans do not know anyone who uses gender-neutral pronouns (Minkin and Brown 2021). This is in stark contrast to most people’s experience with other kinds of minoritized groups (e.g., in the case of racism or sexism). Americans who do know at least one person who uses gender-neutral pronouns likely know very few, also limiting their ability to form accurate productivity-related statistical priors. Hence, it would be impossible for most Americans to form accurate statistical priors about this group that are not informed by stereotypes or preferences.

In terms of discrimination magnitude, I find that discrimination against applicants who disclose “they/them” pronouns is of similar magnitude to discrimination faced by males in non-dominated and female-dominated occupations, and females in male-dominated occupations. Discrimination also builds when applicants have multiple minoritized identities: applicants who disclose nonbinary pronouns, and who are the minoritized sex in a male- or female-dominated occupation, are doubly disadvantaged. This highlights the importance of intersecting minoritized identities in the context of discrimination.

This study shows that there is meaningful discrimination against applicants who disclose “they/them” pronouns during the hiring process. This should motivate additional research which seeks to understand why discrimination exists against this group and what can be done to reduce discrimination. What information is conveyed to employers when applicants disclose pronouns? How can negative stereotypes be reversed and minds changed? I am excited to see large-scale surveys and administrative data beginning to include questions about gender identity in addition to sex. This kind of data, which is currently very difficult to come across, will enable additional investigation on a severely under-researched group.

5 References

Antecol, H., Jong, A., and Steinberger, M. (2008). The sexual orientation wage gap: The role of occupational sorting and human capital. *Industrial and Labor Relations Review*, 61(4):518–543.

Baert, S. (2018). *Hiring discrimination: An overview of (almost) all correspondence experiments since 2005*, pages 63–77.

Bailar, S. (2021). For all the people asking how to use the new instagram function to put your pronouns in your bio, swipe through! [@pinkmantaray]. https://www.instagram.com/p/COyCzYUnWaS/. Accessed October 18, 2023.

Ballard, J. (2022). How Americans feel about gender-neutral pronouns in 2022. YouGov. https://today.yougov.com/politics/articles/43310-how-americans-gender-neutral-pronouns-2022-poll. Accessed October 18, 2023.

Becker, G. S. (1957). *The economics of discrimination*. University of Chicago press.

Bertrand, M. and Mullainathan, S. (2004). Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination. *American Economic Review*, 94(4):991–1013.

Black, D. A., Makar, H. R., Sanders, S. G., and Taylor, L. J. (2003). The earnings effects of sexual orientation. *Industrial and Labor Relations Review*, 56(3):449–469.

Brown, A. (2022). About 5% of young adults in the U.S. say their gender is different from their sex assigned at birth. Pew Research Center. https://www.pewresearch.org/short-reads/2022/06/07/about-5-of-young-adults-in-the-u-s-say-their-gender-is-different-from-their-sex-assigned-at-birth/. Accessed October 18, 2023.

Carpenter, C., Lee, M., and Nettuno, L. (2022). Economic outcomes for transgender people and other gender minorities in the United States: First estimates from a nationally representative sample. *Southern Economic Journal*, 89.

Carpenter, C. S., Eppink, S. T., and Gonzales, G. (2020). Transgender status, gender identity, and socioeconomic outcomes in the United States. *ILR Review*, 73(3):573–599.

Cortina, C., Rodríguez, J., and González, M. J. (2021). Mind the job: The role of occupational characteristics in explaining gender discrimination. *Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement*, 156(1):91–110.

Denier, Nicole ; Waite, S. (2017). Sexual orientation wage gaps across local labour market contexts: Evidence from Canada. *Relations industrielles / Industrial Relations*, 72(4):734–762.

Drydakis, N. (2012). Sexual orientation and labour relations: New evidence from Athens, Greece. *Applied Economics*, 44(20):2653–2665.

Drydakis, N. (2021). Sexual orientation and earnings: A meta-analysis 2012-2020. *Journal of Population Economics*.

Duflo, E., Banerjee, A., Finkelstein, A., Katz, L. F., Olken, B. A., and Sautmann, A. (2020). In praise of moderation: Suggestions for the scope and use of Pre-Analysis Plans for RCTs in economics. https://www.nber.org/papers/w26993. Working Paper.

Eames, T. (2023). Nonbinary hiring discrimination and the politicization of pronouns: A resume audit study. AEA RCT Registry. May 17, 2023. https://doi.org/10.1257/rct.11183-2.0.

FindErnest (2023). Are your resumes being rejected by ATS systems? Indeed. https://www.linkedin.com/pulse/your-resumes-being-rejected-ats-systems-findernest/. Accessed March 5, 2024.

Flage, A. (2019). Discrimination against gays and lesbians in hiring decisions: A meta-analysis. *International Journal of Manpower*, ahead-of-print.

Gaddis, M. S. (2017). How Black are Lakisha and Jamal? Racial perceptions from names used in correspondence audit studies. *Sociological Science*, 4(19):469–489.

Galanes, P. (2021). Do I really need to state my pronouns? The New York Times. https://www.nytimes.com/2021/04/29/style/pronouns-gender-work-social-qs.html. Accessed October 18, 2023.

Geijtenbeek, L. and Plug, E. (2018). Is there a penalty for registered women? Is there a premium for registered men? Evidence from a sample of transsexual workers. *European Economic Review*, 109:334–347. Gender Differences in the Labor Market.

Gelpi, M., Fidas, D., Perrou, M., Shelef, N., and Viverito, C. (2020). What's your pronoun? Strategies for inclusion in the workplace. Out & Equal. https://outandequal.org/wp-content/uploads/2020/05/Pronouns-Guide.pdf. Accessed October 18, 2023.

Gift, K. and Gift, T. (2015). Does politics influence hiring? Evidence from a randomized experiment. *Political Behavior*, 37(3):653–677.

GLAAD (2021). Tips for allies of transgender people. https://glaad.org/transgender/allies/. Accessed October 18, 2023.

Granberg, M., Andersson, P. A., and Ahmed, A. (2020). Hiring discrimination against transgender people: Evidence from a field experiment. *Labour Economics*, 65:101860.

Heckman, J. J. (1998). Detecting discrimination. *The Journal of Economic Perspectives*, 12(2):101–116.

Heckman, J. J. and Siegelman, P. (1993). The Urban Institute audit studies: Their methods and findings.

James, S. E., Herman, J. L., Rankin, S., Keisling, M., Mottet, L., and Anaf, M. (2016). The report of the 2015 U.S. Transgender Survey. National Center for Transgender Equality. https://transequality.org/sites/default/files/docs/usts/USTS-Full-Report-Dec17.pdf. Accessed February 5, 2023.

Jepsen, C. and Jepsen, L. (2022). Convergence over time or not? U.S. wages by sexual orientation, 2000–2019. *Labour Economics*, 74:102086.

Kline, P., Rose, E. K., and Walters, C. R. (2022). Systemic Discrimination Among Large U.S. Employers. *The Quarterly Journal of Economics*, 137(4):1963–2036.

Kohler, C. (2021). Should I put my pronouns on my resume? TopResume. https://ca.topresume.com/career-advice/pronouns-on-resume. Accessed October 13, 2023.

Lahey, J. and Beasley, R. A. (2009). Computerizing audit studies. *Journal of Economic Behavior & Organization*, 70(3):508–514.

Leppel, K. (2016). The labor force status of transgender men and women. *International Journal of Transgenderism*, 17(3-4):155–164.

Leppel, K. (2021). Transgender men and women in 2015: Employed, unemployed, or not in the labor force. *Journal of Homosexuality*, 68(2):203–229. PMID: 31403900.

Mahtani, R. (2022). Should you list your preferred pronouns on your resume? Resume Worded. https://resumeworded.com/blog/preferred-pronouns-on-your-resume/. Accessed October 13, 2023.

McGonagill, R. (2023). Job-seekers with nonbinary gender pronouns on their resumes are less likely to be contacted by employers. Business.com. https://www.business.com/hiring/nonbinary-discrimination-job-market-report/. Accessed February 5, 2023.

Minkin, R. and Brown, A. (2021). Rising shares of U.S. adults know someone who is transgender or goes by gender-neutral pronouns. https://www.pewresearch.org/short-reads/2021/07/27/rising-shares-of-u-s-adults-know-someone-who-is-transgender-or-goes-by-gender-neutral-pronouns/. Accessed March 8, 2024.

Minkin, R. and Brown, A. (n.d.). Sexual orientation and gender identity (SOGI) discrimination. U.S. Equal Employment Opportunity Commission. https://www.eeoc.gov/sexual-orientation-and-gender-identity-sogi-discrimination. Accessed March 9, 2024.

MIT Election Data and Science Lab (2018). County Presidential Election Returns 2000-2020. https://doi.org/10.7910/DVN/VOQCHQ. Accessed February 1, 2022.

Movement Advancement Project (2023). Equality maps: Nondiscrimination laws. https://www.lgbtmap.org/equality-maps/non_discrimination_laws. Accessed February 24, 2023.

Myers, S. (2023). 2023 applicant tracking system (ATS) usage report: Key shifts and strategies for job seekers. JobScan. https://www.jobscan.co/blog/fortune-500-use-applicant-tracking-systems/. Accessed March 5, 2024.

National Center for O*NET Development (2023). Work activities: Performing for or working directly with the public. O*NET OnLine. https://www.onetonline.org/find/descriptor/result/4.A.4.a.8. Accessed February 5, 2023.

National Center for Transgender Equality (2016). Frequently asked questions about transgender people. https://transequality.org/issues/resources/frequently-asked-questions-about-transgender-people. Accessed March 9, 2024.

Nauze, A. L. (2015). Sexual orientation–based wage gaps in Australia: The potential role of discrimination and personality. *The Economic and Labour Relations Review*, 26(1):60–81.

Neumark, D. (2012). Detecting discrimination in audit and correspondence studies. *The Journal of Human Resources*, 47(4):1128–1157.

Neumark, D., Burn, I., and Button, P. (2016). Experimental age discrimination evidence and the Heckman critique. *American Economic Review*, 106(5):303–08.

Neumark, D., Burn, I., and Button, P. (2019). Is it harder for older workers to find jobs? New and improved evidence from a field experiment. *Journal of Political Economy*, 127(2):922 – 970.

Newman, L. S., Tan, M., Caldwell, T. L., Duff, K. J., and Winer, E. S. (2018). Name norms: A guide to casting your next experiment. *Personality and Social Psychology Bulletin*, 44(10):1435–1448. PMID: 29739295.

Niche (2023). 2023 best public high schools in america. https://www.niche.com/k12/search/best-public-high-schools/. Accessed April 15, 2023.

Parker, K., Horowitz, J. M., and Brown, A. (2022). Americans' complex views on gender identity and transgender issues. Pew Research Center. https://www.pewresearch.org/social-trends/2022/06/28/americans-complex-views-on-gender-identity-and-transgender-issues/. Accessed October 18, 2023.

Pollitt, A. M., Ioverno, S., Russell, S. T., Li, G., and Grossman, A. H. (2021). Predictors and mental health benefits of chosen name use among transgender youth. *Youth & Society*, 53(2):320–341.

Resume Builder (2022). 1 in 3 hiring managers more likely to interview people who include pronouns on resume. https://www.resumebuilder.com/pronouns-on-resume/. Accessed March 5, 2024.

Rich, J. (2014). What do field experiments of discrimination in markets tell us? A meta analysis of studies conducted since 2000. IZA Discussion Papers 8584.

Rorris-Crow, A. (2022). Should I put my pronouns on my resume? Ask the "queer career coach". The Muse. https://www.themuse.com/advice/pronouns-on-resume. Accessed October 13, 2023.

Ruggles, S., Flood, S., Sobek, M., Backman, D., Chen, A., Cooper, G., Richards, S., Rogers, R., and Schouweiler, M. (2023). OCC and OCCSOC: Codes for occupation (OCC) and SOC occupation (OCCSOC) in the 2000 Census and the ACS/PRCS samples from 2000 onward. IPUMS USA: Version 14.0. Minneapolis, MN. https://usa.ipums.org/usa/volii/occtooccsoc18.shtml. Accessed February 5, 2023.

Schilt, K. and Wiswall, M. (2008). Before and after: Gender transitions, human capital, and workplace experiences. *The B.E. Journal of Economic Analysis & Policy*, 8(1).

Schmutz, B., Sidibé, M., and Élie Vidal-Naquet (2021). Why are low-skilled workers less mobile? The role of mobility costs and spatial frictions. *Annals of Economics and Statistics*, (142):283–304.

Shannon, M. (2022). The labour market outcomes of transgender individuals. *Labour Economics*, 77:102006.

Tilcsik, A. (2011). Pride and prejudice: Employment discrimination against openly gay men in the united states. *AJS; American journal of sociology*, 117:586–626.

Tucker, L. and Jones, J. (2023). Pronoun lists in profile bios display increased prevalence, systematic co-presence with other keywords and network tie clustering among US Twitter users 2015-2022. *Journal of Quantitative Description: Digital Media*, 3.

U.S. Census Bureau (2020). TIGERweb state-based data files: County-Census 2020. https://tigerweb.geo.census.gov/tigerwebmain/TIGERweb_counties_census2020.html. Accessed February 1, 2022.

U.S. Census Bureau (2021). Frequently occurring surnames from the 2010 Census. https://www.census.gov/topics/population/genealogy/data/2010_surnames.html. Accessed April 5, 2023.

U.S. Census Bureau (2022a). Census Bureau releases new educational attainment data. https://www.census.gov/newsroom/press-releases/2022/educational-attainment.html. Accessed October 25, 2023.

U.S. Census Bureau (2022b). Detailed occupation by sex education age earnings: ACS 2019. https://www.census.gov/data/tables/2022/demo/acs-2019.html. Accessed February 5, 2023.

U.S. Census Bureau (2023). County population by characteristics: 2020-2022. https://www.census.gov/data/tables/time-series/demo/popest/2020s-counties-detail.html. Accessed March 9, 2024.

US Deparmtnet of Agriculture (2023). County-level data sets: Download data. Economic Research Service. https://www.ers.usda.gov/data-products/county-level-data-sets/county-level-data-sets-download-data/. Accessed March 9, 2024.

US Religious Census (2020). Maps and data files for 2020. https://www.usreligioncensus.org/node/1639. Accessed March 9, 2024.

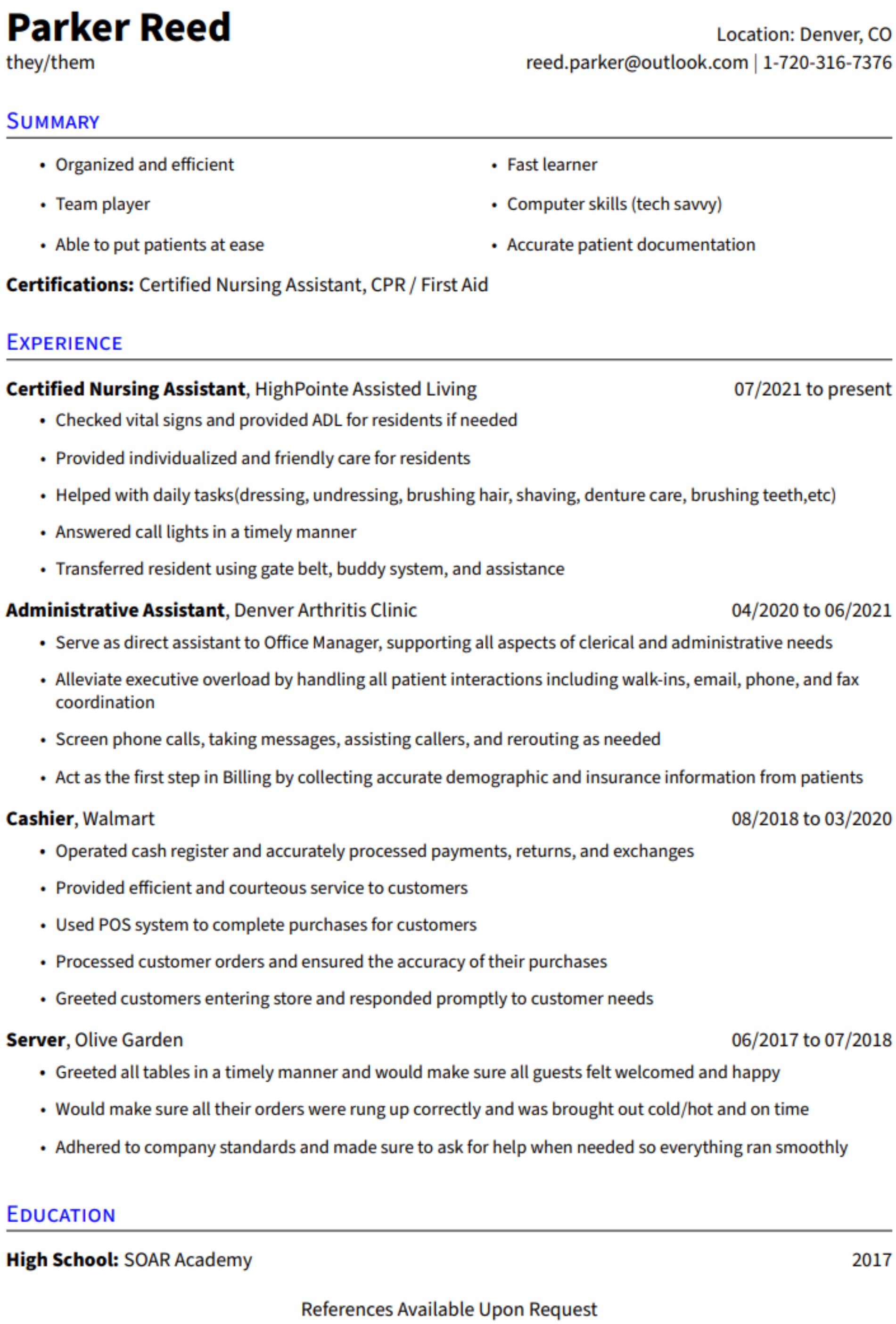
U.S. Social Security (2023). Top names of the 1990s. https://www.ssa.gov/oact/babynames/decades/names1990s.html. Accessed April 5, 2023.

Waite, S., Ecker, J., and Ross, L. E. (2019). A systematic review and thematic synthesis of Canada's LGBTQ2S+ employment, labour market and earnings literature. *PLOS ONE*, 14(10):1–20.

Wilson, B. D. and Meyer, I. H. (2021). Brief: Nonbinary LGBTQ adults in the United States. The Williams Institute. https://williamsinstitute.law.ucla.edu/publications/nonbinary-lgbtq-adults-us/. Accessed October 18, 2023.

Yavorsky, J. E. (2019). Uneven patterns of inequality: An audit analysis of hiring-related practices by gendered and classed contexts. *Social Forces*, 98(2):461–492.

Figures



Parker Reed

they/them

Location: Denver, CO
reed.parker@outlook.com | 1-720-316-7376

Summary

- Organized and efficient
- Fast learner
- Team player
- Computer skills (tech savvy)
- Able to put patients at ease
- Accurate patient documentation

Certifications: Certified Nursing Assistant, CPR / First Aid

Experience

Certified Nursing Assistant, HighPointe Assisted Living — 07/2021 to present

- Checked vital signs and provided ADL for residents if needed
- Provided individualized and friendly care for residents
- Helped with daily tasks(dressing, undressing, brushing hair, shaving, denture care, brushing teeth,etc)
- Answered call lights in a timely manner
- Transferred resident using gate belt, buddy system, and assistance

Administrative Assistant, Denver Arthritis Clinic — 04/2020 to 06/2021

- Serve as direct assistant to Office Manager, supporting all aspects of clerical and administrative needs
- Alleviate executive overload by handling all patient interactions including walk-ins, email, phone, and fax coordination
- Screen phone calls, taking messages, assisting callers, and rerouting as needed
- Act as the first step in Billing by collecting accurate demographic and insurance information from patients

Cashier, Walmart — 08/2018 to 03/2020

- Operated cash register and accurately processed payments, returns, and exchanges
- Provided efficient and courteous service to customers
- Used POS system to complete purchases for customers
- Processed customer orders and ensured the accuracy of their purchases
- Greeted customers entering store and responded promptly to customer needs

Server, Olive Garden — 06/2017 to 07/2018

- Greeted all tables in a timely manner and would make sure all guests felt welcomed and happy
- Would make sure all their orders were rung up correctly and was brought out cold/hot and on time
- Adhered to company standards and made sure to ask for help when needed so everything ran smoothly

Education

High School: SOAR Academy — 2017

References Available Upon Request

Figure 1: Resume Format 1 Example

Adrian Nelson
Denver, CO | adrian.m.nelson@outlook.com | (720)-738-0456

Work Experience

September 2021 - Present The University of Colorado Hospital, Certified Nursing Assistant

– Complete administrative within the department
– Monitor patient heart rhythms and oxygen levels and escalate as appropriate
– Maintain solid communication with patients, visitors, nursing staff, and interdisciplinary team members
– Assist patients with activities of daily living and provide basic nursing care
– Assist in maintenance of a safe and clean environment

July 2020 - August 2021 Target, Cashier

– Operated cash register or POS system to receive payment by cash, check and credit card
– Helped customers find specific products, answered questions and offered product advice
– Completed daily recovery tasks to keep areas clean and neat for maximum productivity
– Preserved appearance of store by arranging and replenishing displays and merchandise racks

April 2019 - June 2020 Wendy's, Crew Member

– Take customer orders, prepare food made to order, and provide customer service
– Clean the dining room, service counter, and kitchen stations
– Depending on the shift, had to carry out opening or closing duties

August 2017 - March 2019 Outback Steakhouse, Host

– Responsible for greeting and seating customers, including managing wait lists
– Coordinate with serving staff to ensure a smooth and satisfactory service
– Answered phones, recorded reservations, and resolved customer issues

Education

2017 Addenbrooke Classical Academy: High School Diploma

Skills

Detail oriented, Strong work ethic, Caring and compassionate, Works well under pressure, Clear communicator, Prioritize patient care and comfort
Certifications: CNA, CPR

Figure 2: Resume Format 2 Example

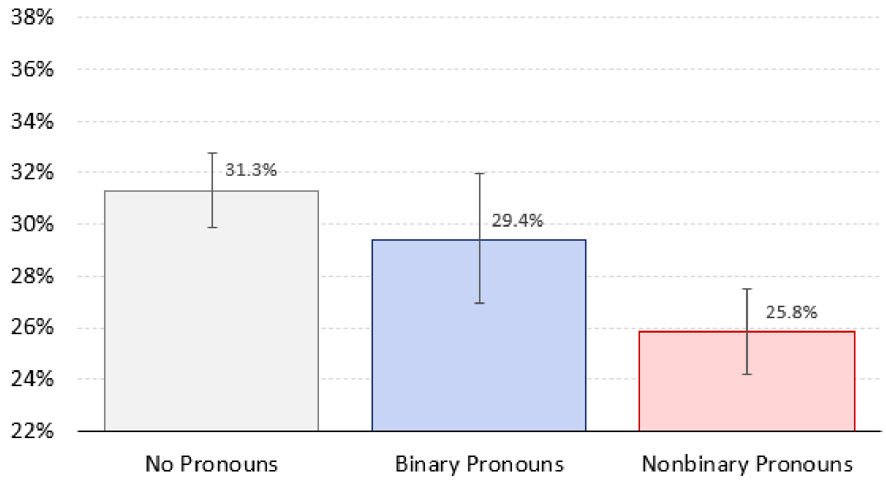


Figure 3: Positive Employer Response by Pronoun Disclosure

Note: This figure reports positive employer response rates for treatment and control groups. Whiskers show the 95% confidence interval associated with the true positive employer response rate for each group, calculated using the normal approximation to the binomial distribution.

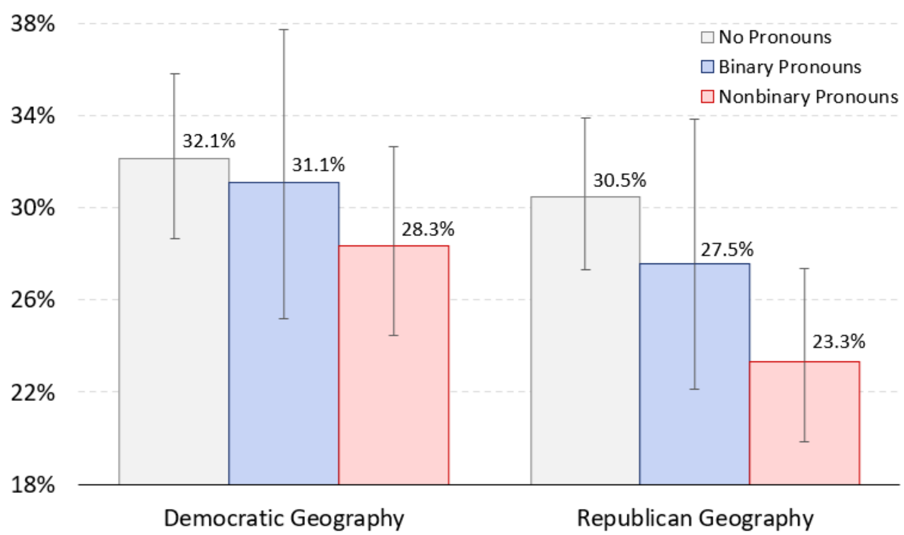


Figure 4: Positive Employer Response Rates by Pronoun Disclosure and Geographic Politics

Note: This figure reports positive employer response rates for treatment and control groups, for implied male and female applicants. Whiskers show the 95% confidence interval associated with the true positive employer response rate for each group, calculated using the normal approximation to the binomial distribution.

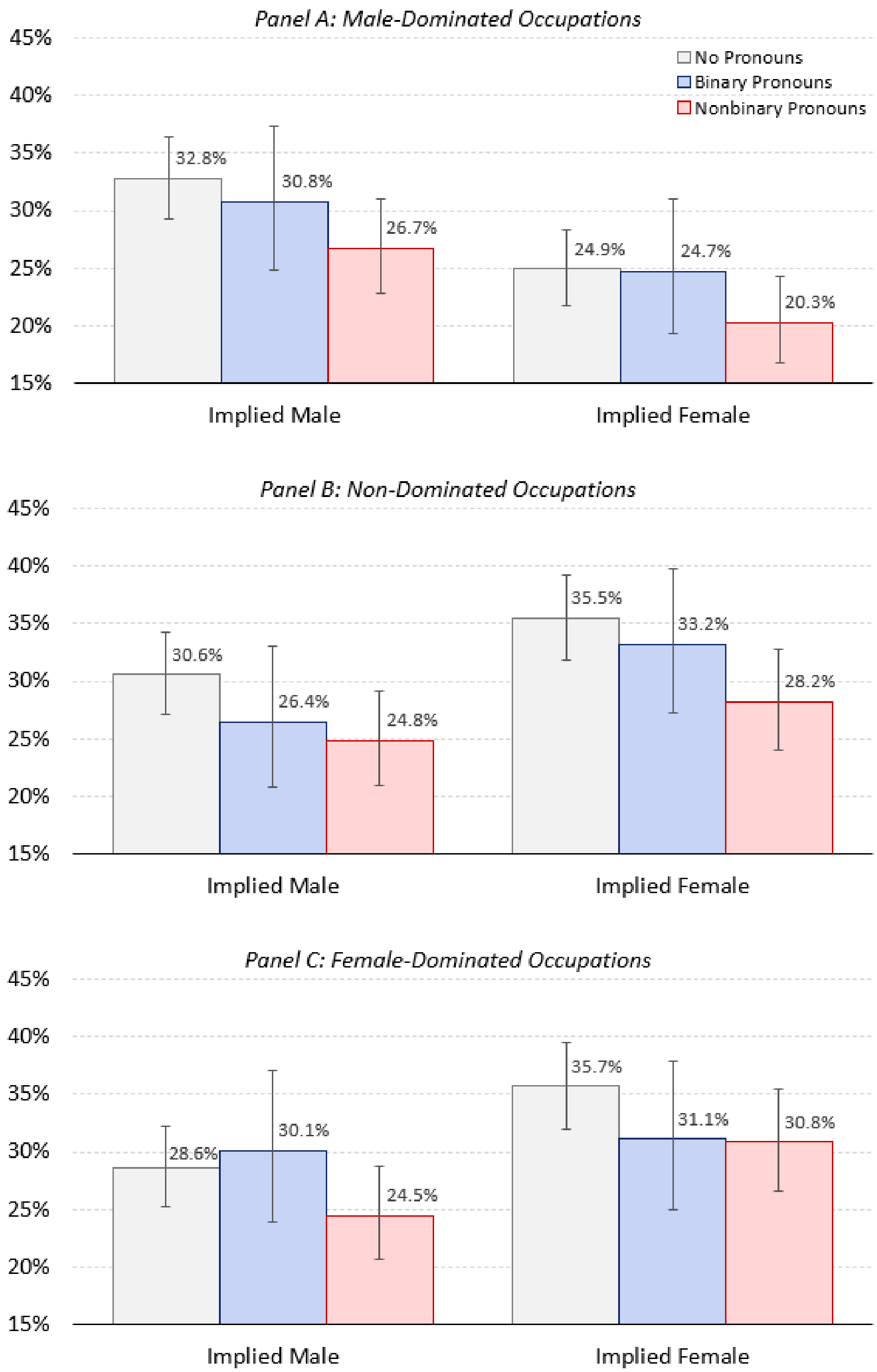


Figure 5: Positive Employer Response Rates by Pronoun Disclosure and Implied Sex

Note: This figure reports positive employer response rates for treatment and control groups, for implied male and female applicants. Whiskers show the 95% confidence interval associated with the true positive employer response rate for each group, calculated using the normal approximation to the binomial distribution.

Tables

Table 1: First Names

		1990s Baby Name Popularity		Name Association Scores	
Implied Sex	First Name	Rank	Count (1,000s)	Warmth	Competence
Male	Patrick	42	93	3.23	3.15
Male	Jeremy	47	78	3.12	3.05
Male	Marcus	83	46	3.14	3.01
Male	Adrian	92	42	3.10	3.02
Male	Joel	112	34	3.24	3.12
Male	Parker	195	16	3.25	3.17
Female	Hannah	11	159	3.14	3.05
Female	Jasmine	25	105	2.87	3.09
Female	Leah	97	34	3.13	3.11
Female	Lindsay	104	31	3.13	3.00
Female	Marisa	188	16	3.07	3.18
Female	Gina	199	15	2.96	3.10

Note: rank is the rank of name popularity among babies born in the 1990s (where 1 is the most popular name); count is the count of babies born in the 1990s with that name; data is sourced from U.S. Social Security (2023). Data on name association scores (warmth and competency) is sourced from Newman et al. (2018). Note that the name Jasmine has been used to signal an applicant is Black in previous correspondence studies; however, Gaddis (2017) shows that it is a poor Black signal.

Table 2: Last Names

	Name Popularity		Racial Composition		
Last Name	Rank	Count (1,000s)	% White	% African American	% Hispanic
Anderson	15	784	75.2	18.9	2.1
Thomas	16	756	52.6	38.8	2.6
Lewis	29	532	582	34.8	2.6
Allen	33	483	67.6	26.2	2.4
Nelson	43	425	77.7	16.0	2.0
Campbell	47	386	73.7	20.5	2.1
Phillips	52	361	76.7	17.1	2.2
Collins	59	330	71.6	22.4	2.2
Morris	62	319	73.6	20.1	2.2
Reed	73	277	71.3	22.6	2.3
Watson	81	253	66.0	27.9	2.3
James	85	249	51.6	38.9	2.6

Note: rank is the rank of name popularity among the United States population (where 1 is the most popular name); count is the count of people with that last name; data is sourced from U.S. Census Bureau (2021).

Table 3: Full Names

Full Name	State	Implied Sex	Email	Order
Marcus Thomas	Washington (WA)	Male	marcus.h.thomas@outlook.com	First
Patrick Lewis	Washington (WA)	Male	patrick.d.lewis@outlook.com	Second
Lindsay Campbell	Washington (WA)	Female	lindsay.a.campbell@outlook.com	First
Jasmine Phillips	Washington (WA)	Female	jasmine.m.phillips@outlook.com	Second
Joel Morris	Utah (UT)	Male	morris.d.joel@outlook.com	First
Jeremy Anderson	Utah (UT)	Male	jeremy.a.anderson@outlook.com	Second
Hannah Allen	Utah (UT)	Female	allen.l.hannah@outlook.com	First
Leah James	Utah (UT)	Female	leah.m.james@outlook.com	Second
Parker Reed	Colorado (CO)	Male	reed.parker@outlook.com	First
Adrian Nelson	Colorado (CO)	Male	adrian.m.nelson@outlook.com	Second
Marisa Watson	Colorado (CO)	Female	watson.e.marisa@outlook.com	First
Gina Collins	Colorado (CO)	Female	collins.gina@outlook.com	Second

Note: order denotes the order applications were sent in; for example, when applying as a female in Washington state, whichever resume is randomly assigned the name Lindsay Campbell will apply for the job first. This is described in more detail in Section 1.4.

Table 4: Geographies

	Population		Adjusted Republican Presidential Vote Share (%)						
CBSA	Count (1,000s)	Density	2000	2004	2008	2012	2016	2020	Category
Seattle-Tacoma-Bellevue, WA	4,034	687	40	40	34	35	31	31	Democratic
Spokane-Spokane Valley, WA	612	108	56	57	52	54	57	54	Republican
Salt Lake City, UT	1,266	165	62	62	51	61	45	46	Democratic
Provo-Orem, UT	715	133	85	88	80	90	78	72	Republican
Denver-Aurora-Lakewood, CO	2,986	358	50	49	41	43	41	37	Democratic
Colorado Springs, CO	765	285	68	68	60	61	63	56	Republican

Note: Core Based Statistical Area (CBSA) population data is listed in thousands and sourced from the U.S. Census Bureau (2023). Population density is people per square mile, where square miles are sourced from TIGERweb U.S. Census Bureau (2020). Annual Presidential voting records is sourced from MIT Election Data and Science Lab (2018) and adjusted such that Republican and Democratic vote shares sum to 1.

Table 5: Occupations

Occupation	Worker Composition		Customer Interaction	
	% Male	Category	Score	Category
Construction Worker	97	Male-Dominated	59	Medium
Truck Driver	95	Male-Dominated	53	Medium
Warehouse Worker	80	Male-Dominated	46	Low
Janitor	70	Male-Dominated	44	Low
Landscaper	94	Male-Dominated	32	Low
Retail Salesperson	62	Non-Dominated	93	High
Server	36	Non-Dominated	75	High
Cook	59	Non-Dominated	52	Medium
Baker	44	Non-Dominated	37	Low
Assembler / Fabricator	62	Non-Dominated	17	Low
Receptionist	9	Female-Dominated	87	High
Cashier	28	Female-Dominated	86	High
Housekeeper	15	Female-Dominated	58	Medium
Certified Nursing Assistant	11	Female-Dominated	47	Low
Administrative Assistant	6	Female-Dominated	47	Low

Note: worker count and composition data is from the 2019 American Community Survey (U.S. Census Bureau 2022b). Customer Interaction scores are from the Occupational Information Network (O*NET), representing the importance of "performing for people or working directly with the public. This includes serving customers in restaurants and stores, and receiving clients or guests" (National Center for O*NET Development 2023). A crosswalk matching occupation codes between ACS and O*NET was sourced from Ruggles et al. (2023). For the Cook, Truck Driver, and Warehouse Worker occupations, ACS codes were mapped to multiple O*NET occupation codes. In these cases, the O*NET score was averaged across mapped codes.

Table 6: Count of Paired Resumes, Nonbinary "they/them" Pronoun Treatment

Occupation	Count per Occupation and City						
	Seattle	Spokane	Salt Lake City	Provo	Denver	Colorado Springs	All
Receptionist	36	33	30	35	32	35	201
Cashier	25	24	23	23	23	21	139
Housekeeper	25	23	25	32	24	22	151
Certified Nursing Assistant	48	45	34	50	45	39	261
Administrative Assistant	26	25	23	21	27	25	147
Retail Sales	56	53	57	57	53	58	334
Server	23	25	20	22	19	23	132
Cook	31	42	41	41	33	39	227
Baker	9	12	14	12	10	9	66
Assembler / Fabricator	19	17	17	17	20	15	105
Construction Worker	23	24	22	24	23	25	141
Truck Driver	45	47	50	43	42	40	267
Warehouse Worker	37	38	37	33	35	37	217
Janitor	24	23	24	31	30	30	162
Landscaper	26	26	25	20	26	22	145
Total	453	457	442	461	442	440	2695

Table 7: Count of Paired Resumes, Binary "he/him" or "she/her" Pronoun Treatment

	Count per Occupation and City						
Occupation	Seattle	Spokane	Salt Lake City	Provo	Denver	Colorado Springs	All
Receptionist	14	16	21	15	18	14	98
Cashier	5	5	8	5	7	8	38
Housekeeper	13	15	13	7	14	16	78
Certified Nursing Assistant	16	19	28	13	19	25	120
Administrative Assistant	10	11	14	15	9	12	71
Retail Sales	28	29	27	27	30	25	166
Server	10	9	12	11	15	11	68
Cook	27	16	17	17	25	17	119
Baker	6	3	3	4	6	5	27
Assembler	9	10	11	11	7	13	61
Construction Worker	12	12	14	13	13	10	74
Truck Driver	21	18	15	25	24	26	129
Warehouse Worker	19	17	20	23	21	18	118
Janitor	12	12	14	6	6	5	55
Landscaper	9	10	10	15	10	14	68
Total	211	202	227	207	224	219	1290

Table 8: Resume Characteristics (X_i Control Variables)

Variable	Type	Description
Occupation	Fixed Effect	Fixed effects for each of the 15 occupations being applied for
Location	Fixed Effect	Fixed effects for each of the six cities being applied within
Research Assistant	Fixed Effect	Fixed effects for each Research Assistant who found and applied to the job posting
Sent first	Indicator	Equals 1 if the resume was sent first
Resume lag	Discrete	Equals 0 if the resume was sent first, and the hours between the first and second application if the resume was sent second
Resume lag^2	Discrete	Above squared
GED	Indicator	Equals 1 if the applicant achieved a GED
Associate's	Indicator	Equals 1 if the applicant achieved an Associate's degree
Bachelor's	Indicator	Equals 1 if the applicant achieved a Bachelor's degree
High Score High School	Indicator	Equals 1 if the applicant went to a high school with test scores rated 'A' by Niche
Low Score High School	Indicator	Equals 1 if the applicant went to a high school with test scores rated 'C' or below by Niche
Worked in HS	Indicator	Equals 1 if the applicant worked during high school
Years relevant	Discrete	Equals the number of years of "relevant" work experience.
Years relevant^2	Discrete	Above squared
Current relevant	Indicator	Equals 1 if the applicant's most recent work experience is "relevant"
Current most common	Indicator	Equals 1 if the applicant's most recent work experience is "most common"
Current common	Indicator	Equals 1 if the applicant's most recent work experience is "common"
Prior most common	Discrete	Equals the years of "most common" experience, omitting most recent experience
Prior most common^2	Discrete	Above squared
Prior common	Discrete	Equals the years of "common" experience, omitting most recent experience
Prior common^2	Discrete	Above squared
Summary	Indicator	Equals 1 if the resume includes a summary or objective section
Skill: communication	Indicator	Equals 1 if the applicant's resume lists "clear communicator" as a skill
Skill: computer	Indicator	Equals 1 if the applicant's resume lists "computer skills (tech savvy)" as a skill
Skill: detail oriented	Indicator	Equals 1 if the applicant's resume lists "detail oriented" as a skill
Skill: fast learner	Indicator	Equals 1 if the applicant's resume lists "fast learner" as a skill
Skill: fast-paced	Indicator	Equals 1 if the applicant's resume lists "thrives in fast-paced settings" as a skill
Skill: leader	Indicator	Equals 1 if the applicant's resume lists "leadership abilities" as a skill
Skill: organized	Indicator	Equals 1 if the applicant's resume lists "organized and efficient" as a skill
Skill: team player	Indicator	Equals 1 if the applicant's resume lists "team player" as a skill

Note: Work experience is considered "relevant" if it is in the position being applied for (e.g., if an applicant is applying to a janitor position, janitorial experience is "relevant"). Work experience is considered "most common" if it is in the position observed to be most common among non-"relevant" past experiences. This position is occupation-specific, and identified from the resume-scraping process described in Section 1.1.5: of the 12 positions identified for each occupation, this position is most commonly observed before the worker obtained a job in the occupation of interest. Work experience is defined as "common" if it is the second or third most common position. Identifying relevant and common positions is done to control for past work experience in a way that is consistent across occupations. These variables are included in lieu of position fixed effects because experience in a given position influences the probability of positive employer response heterogeneously across occupations. For example, cashier experience may be seen as generally relevant when applying as a sales associate but generally irrelevant when applying as a janitor.

Table 9: Firm and Job Characteristics (Z_j Control Variables)

Variable	Type	Description
Occupation	Fixed Effect	Fixed effects for each of the 15 occupations being applied for
Location	Fixed Effect	Fixed effects for each of the six cities being applied within
Research Assistant	Fixed Effect	Fixed effects for each Research Assistant who found and applied to the job posting
Estimated applications	Discrete	Equals the lower bound of the range of applicants estimated to have applied to the job posting (this was scraped from the job board website, values range from 1 to 1,496). Equals 0 if the job board website did provide an estimated application range
Estimated applications^2	Discrete	Above squared
Missing estimated applications	Indicator	Equals 1 if the job board did not provide an estimated application range
Relative income	Continuous	The lower bound of estimated income expressed as a percent of the occupation-specific average
Relative income^2	Continuous	Above squared
Relative income difference	Continuous	The difference between the upper and lower estimated income bounds expressed as a percent of the occupation-specific average
Relative income difference^2	Continuous	Above squared
Missing estimated income	Indicator	Equals 1 if the job posting did not include an associated income range

Table 10: Interaction Variables

Notation	Indicator Variable	Description
R_j	Republican Geography	Equals 1 if the job is located in a Republican geography (Spokane, WA; Provo, UT; Colorado Springs, CO)
M_i	Implied Male	Equals 1 if the applicant is implied to be male (through name assignment)
MD_j	Male-Dominated	Equals 1 if the applicant is applying in a male-dominated occupation (construction worker, truck driver, warehouse worker, janitor, landscaper)
FD_j	Female-Dominated	Equals 1 if the applicant is applying in a female-dominated occupation (receptionist, cashier, housekeeper, certified nursing assistant, administrative assistant)
HC_j	High Customer-Facing	Equals 1 if the applicant is applying in a high customer interaction occupation (receptionist, cashier, retail salesperson, server)
LC_j	Low Customer-Facing	Equals 1 if the applicant is applying in a low customer interaction occupation (certified nursing assistant, administrative assistant, baker, assembler / fabricator, warehouse worker, janitor, landscaper)

Table 11: Interaction Variables (Continuous Versions)

Indicator Variable	Continuous Replacement	Description
R_j	Republican Vote Share	Equals the Republican vote share in a CBSA, adjusted such that Republican and Democratic vote shares sum to 1
MD_j, FD_j	Percent Male	Equals the percent of the workforce in the occupation who is male
HC_j, LC_j	O*NET Score	O*NET score representing the importance of "performing for people or working directly with the public. This includes serving customers in restaurants and stores, and receiving clients or guests" (National Center for O*NET Development 2023). A crosswalk matching occupation codes between ACS and O*NET was sourced from Ruggles et al. (2023). For the Cook, Truck Driver, and Warehouse Worker occupations, ACS codes were mapped to multiple O*NET occupation codes. In these cases, O*NET score was averaged across mapped codes.

Table 12: Differences in Positive Employer Response by Group

	Positive Employer Response					Sample Size		
Observations	NP	NB	NB - NP	B	B - NP	NP	NB	B
All Observations	0.313	0.258	-0.055 ***	0.294	-0.019	3985	2695	1290
			(0.011)		(0.033)			
Implied Males	0.307	0.253	-0.053 ***	0.291	-0.016	1994	1365	629
			(0.016)		(0.040)			
Implied Females	0.319	0.263	-0.056 ***	0.297	-0.022	1991	1330	661
			(0.016)		(0.038)			
Democratic City	0.321	0.283	-0.038 **	0.311	-0.010	1999	1337	662
			(0.016)		(0.035)			
Republican City	0.305	0.233	-0.071 ***	0.275	-0.029	1986	1358	628
			(0.016)		(0.043)			
Male-Dominated	0.289	0.235	-0.054 ***	0.277	-0.011	1376	932	444
			(0.019)		(0.047)			
Non-Dominated	0.330	0.265	-0.065 ***	0.299	-0.031	1305	864	441
			(0.020)		(0.044)			
Female-Dominated	0.321	0.276	-0.045 **	0.306	-0.015	1304	899	405
			(0.020)		(0.043)			
High Customer Facing	0.304	0.244	-0.059 ***	0.284	-0.020	1176	806	370
			(0.021)		(0.048)			
Medium Customer Facing	0.293	0.260	-0.034	0.265	-0.028	1186	786	400
			(0.021)		(0.029)			
Low Customer Facing	0.334	0.267	-0.066 ***	0.323	-0.011	1623	1103	520
			(0.018)		(0.053)			

Note: This table reports positive employer response rates for treatment and control groups. Column "NB - NP" reports the difference in response rates between applicants who disclose nonbinary "they/them" pronouns (NB) and those who disclose no pronouns (NP). Column "B - NP" reports the difference in response rates between applicants who disclose binary "he/him" or "she/her" pronouns (B) congruent with name-implied sex and those who disclose no pronouns. Standard errors associated with Chi-squared tests of these difference in proportions are reported in parentheses.

Table 13: Differences in Positive Employer Response by Geography

	Positive Employer Response					Sample Size		
Observations	NP	NB	NB - NP	B	B - NP	NP	NB	B
Washington	0.307	0.251	-0.056 *** (0.020)	0.286	-0.021 (0.044)	1323	910	413
Colorado	0.316	0.259	-0.058 *** (0.020)	0.296	-0.021 (0.045)	1325	882	443
Utah	0.316	0.266	-0.050 ** (0.020)	0.30	-0.016 (0.043)	1337	903	434
Seattle, WA	0.340	0.302	-0.038 (0.029)	0.332	-0.009 (0.054)	664	453	211
Spokane, WA	0.273	0.199	-0.074 *** (0.026)	0.238	-0.036 (0.056)	659	457	202
Denver, CO	0.318	0.294	-0.024 (0.029)	0.304	-0.015 (0.042)	666	442	224
Colorado Springs, CO	0.314	0.223	-0.091 *** (0.028)	0.288	-0.026 (0.070)	659	440	219
Salt Lake City, UT	0.305	0.253	-0.052 * (0.028)	0.30	-0.005 (0.060)	669	442	227
Provo, UT	0.326	0.278	-0.049 * (0.029)	0.30	-0.027 (0.049)	668	461	207

Note: This table reports positive employer response rates by group. Column "NB - NP" reports the difference in response rates between applicants who disclose nonbinary "they/them" pronouns (NB) and those who disclose no pronouns (NP). Column "B - NP" reports the difference in response rates between applicants who disclose binary "he/him" or "she/her" pronouns (B) congruent with name-implied sex and those who disclose no pronouns. Standard errors associated with Chi-squared tests of these difference in proportions are reported in parentheses.

Table 14: Differences in Positive Employer Response by Occupation

	Positive Employer Response					Sample Size		
Observations	NP	NB	NB - NP	B	B - NP	NP	NB	B
Administrative Assistant	0.161	0.116	-0.045	0.197	0.037	218	147	71
			(0.039)		(0.100)			
Construction Worker	0.181	0.163	-0.018	0.189	0.008	215	141	74
			(0.044)		(0.070)			
Receptionist	0.221	0.199	-0.022	0.204	-0.017	299	201	98
			(0.039)		(0.053)			
Server	0.265	0.197	-0.068	0.250	-0.015	200	132	68
			(0.050)		(0.093)			
Janitor	0.286	0.228	-0.057	0.345	0.060	217	162	55
			(0.048)		(0.137)			
Assembler	0.295	0.248	-0.048	0.246	-0.049	166	105	61
			(0.059)		(0.070)			
Landscaper	0.310	0.234	-0.075	0.294	-0.016	213	145	68
			(0.050)		(0.099)			
Truck Driver	0.313	0.262	-0.051	0.279	-0.034	396	267	129
			(0.037)		(0.057)			
Warehouse Worker	0.316	0.253	-0.063	0.288	-0.028	335	217	118
			(0.041)		(0.069)			
Housekeeper	0.319	0.298	-0.021	0.295	-0.024	229	151	78
			(0.051)		(0.063)			
Cook	0.324	0.291	-0.033	0.277	-0.046	346	227	119
			(0.041)		(0.044)			
Retail Sales	0.348	0.263	-0.085 **	0.319	-0.029	500	334	166
			(0.033)		(0.073)			
Cashier	0.362	0.309	-0.052	0.395	0.033	177	139	38
			(0.057)		(0.139)			
Baker	0.462	0.348	-0.114	0.519	0.056	93	66	27
			(0.085)		(0.208)			
Certified Nursing Assistant	0.475	0.395	-0.080 *	0.433	-0.042	381	261	120
			(0.041)		(0.075)			

Note: This table reports positive employer response rates by group. Column "NB - NP" reports the difference in response rates between applicants who disclose nonbinary "they/them" pronouns (NB) and those who disclose no pronouns (NP). Column "B - NP" reports the difference in response rates between applicants who disclose binary "he/him" or "she/her" pronouns (B) congruent with name-implied sex and those who disclose no pronouns. Standard errors associated with Chi-squared tests of these difference in proportions are reported in parentheses.

Table 15: Estimates of Discrimination Against Applicants who Disclose Pronouns

	(A)	(B)	(C)	(D)
Panel A: Disclosing pronouns compared to not disclosing pronouns				
Nonbinary Pronouns	-0.054***	-0.054***	-0.055***	-0.054***
	(0.008)	(0.008)	(0.008)	(0.008)
	[-0.070, -0.039]	[-0.071, -0.038]	[-0.070, -0.040]	[-0.071, -0.038]
Binary Pronouns	-0.018	-0.017	-0.016	-0.017
	(0.012)	(0.012)	(0.011)	(0.011)
	[-0.041, 0.004]	[-0.039, 0.006]	[-0.039, 0.006]	[-0.039, 0.006]
Observations	7970	7970	7970	7970
Panel B: Disclosing nonbinary compared to binary pronouns				
Nonbinary Pronouns	-0.036**	-0.036**	-0.038***	-0.037**
	(0.015)	(0.015)	(0.014)	(0.015)
	[-0.065, -0.006]	[-0.066, -0.007]	[-0.066, -0.010]	[-0.066, -0.008]
Observations	3985	3985	3985	3985
Resume Controls		✓		✓
Firm Controls			✓	✓

Note: Panel A reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns. Marginal effects are derived from the logistic regression described in equation (1). Panel B reports average marginal effects associated with disclosing nonbinary "they/them" pronouns compared to disclosing binary "he/him" or "she/her" pronouns congruent with name-implied sex. Marginal effects are derived from the logistic regression described in equation (2); only treated observations are included. In all panels, the dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table 16: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Geographic Politics

	Nonbinary Pronouns			Binary Pronouns		
	(D1)	(D2)	(D3)	(D1)	(D2)	(D3)
Pronouns	-0.035*** (0.011) [-0.057, -0.014]	-0.005 (0.030) [-0.063, 0.053]	0.197* (0.108) [-0.015, 0.409]	-0.010 (0.016) [-0.041, 0.021]	-0.005 (0.044) [-0.091, 0.082]	0.080 (0.183) [-0.280, 0.439]
Pronouns × Republican Geography	-0.040** (0.016) [-0.071, -0.009]			-0.013 (0.023) [-0.058, 0.032]		
Pronouns × Republican Vote Share		-0.103* (0.059) [-0.219, 0.013]	-0.949** (0.465) [-1.861, -0.038]		-0.024 (0.088) [-0.197, 0.148]	-0.366 (0.694) [-1.727, 0.994]
Pronouns × Republican Vote Share^2			0.827* (0.451) [-0.057, 1.711]			0.334 (0.671) [-0.981, 1.649]
Observations	7970	7970	7970	7970	7970	7970
Resume Controls	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns. Marginal effects are derived from the logistic regression described in equation (4) including only political interactions. The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table 17: County Differences in Democratic and Republican CBSAs

	County-Level Mean		
Variable	Democratic CBSA	Republican CBSA	Difference
Panel A: Counties in all U.S. CBSAs with a CBSA population of at least 500,000			
Population (1,000s)	437.3	201.4	235.9 *** (42.2)
People per Square Mile	1593	363	1230 *** (247)
Median Household Income ($1,000s)	78.3	65.8	12.5 *** (1.3)
Education: Percent Less High School	0.099	0.104	-0.005 (0.004)
Education: Percent Bachelor's or More	0.335	0.262	0.073 *** (0.009)
Percent White	0.755	0.852	-0.096 *** (0.012)
Percent Black	0.158	0.091	0.067 *** (0.011)
Percent Other	0.087	0.057	0.029 *** (0.005)
Religious Congregations per 100K	112	157	-45.2 *** (5.83)
Panel B: Counties in the six study CBSAs			
Population (1,000s)	552.4	298.9	253.5 (219.2)
People per Square Mile	878	155	723 ** (353)
Median Household Income ($1,000s)	93.6	71.5	22.1 *** (6.4)
Education: Percent Less High School	0.064	0.058	0.006 (0.012)
Education: Percent Bachelor's or More	0.424	0.306	0.118 ** (0.051)
Percent White	0.844	0.901	-0.057 * (0.031)
Percent Black	0.04	0.019	0.021 (0.014)
Percent Other	0.116	0.08	0.036 * (0.021)
Religious Congregations per 100K	80	142	-61.7 ** (27.18)

Note: This table reports a range of averages for counties located in Republican versus Democratic Core Based Statistical Areas (CBSAs). A CBSA is considered "Republican" if more votes were cast for the Republican presidential candidate than the Democratic presidential candidate in the 2020 election (vice-versa for "Democratic"). Difference reports the difference in averages, and t-test statistics are also reported: standard errors are listed in parentheses and stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level. Population and race data is sourced from U.S. Census Bureau (2023), land square miles from from TIGERweb U.S. Census Bureau (2020), income and education data from US Deparmtnet of Agriculture (2023), and religious congregation data from US Religious Census (2020).

Table 18: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions

	Nonbinary Pronouns			Binary Pronouns		
	(D1)	(D2)	(D3)	(D1)	(D2)	(D3)
Pronouns	-0.021 (0.023) [-0.067, 0.024]	0.000 (0.044) [-0.086, 0.087]	0.166 (0.137) [-0.102, 0.434]	-0.034 (0.031) [-0.096, 0.027]	-0.002 (0.063) [-0.125, 0.120]	0.063 (0.220) [-0.367, 0.494]
Pronouns × Implied Male	0.004 (0.016) [-0.028, 0.036]	0.004 (0.016) [-0.028, 0.036]	0.004 (0.016) [-0.028, 0.036]	0.001 (0.024) [-0.046, 0.047]	0.001 (0.024) [-0.045, 0.047]	0.001 (0.024) [-0.045, 0.047]
Pronouns × Republican Geography	-0.040** (0.016) [-0.071, -0.009]			-0.014 (0.023) [-0.059, 0.031]		
Pronouns × Republican Vote Share		-0.102* (0.059) [-0.218, 0.014]	-0.948** (0.466) [-1.860, -0.035]		-0.026 (0.088) [-0.199, 0.146]	-0.363 (0.699) [-1.733, 1.007]
Pronouns × Republican Vote Share^2			0.826* (0.451) [-0.059, 1.710]			0.329 (0.676) [-0.995, 1.654]
Pronouns × High Customer Facing	-0.030 (0.022) [-0.074, 0.014]			0.028 (0.036) [-0.042, 0.098]		
Pronouns × Low Customer Facing	-0.036* (0.019) [-0.073, 0.001]			0.022 (0.029) [-0.036, 0.079]		
Pronouns × O*NET Score		0.000 (0.000) [-0.001, 0.001]	0.001 (0.003) [-0.004, 0.007]		0.000 (0.001) [-0.001, 0.001]	0.000 (0.003) [-0.006, 0.007]
Pronouns × O*NET Score^2			0.000 (0.000) [0.000, 0.000]			0.000 (0.000) [0.000, 0.000]
Pronouns × Male-Dominated	0.003 (0.023) [-0.042, 0.048]			0.018 (0.033) [-0.047, 0.082]		
Pronouns × Female-Dominated	0.021 (0.021) [-0.021, 0.063]			0.008 (0.031) [-0.052, 0.068]		
Pronouns × Percent Male		-0.011 (0.026) [-0.062, 0.041]	-0.056 (0.122) [-0.296, 0.184]		-0.007 (0.039) [-0.082, 0.068]	0.028 (0.173) [-0.311, 0.367]
Pronouns × Percent Male^2			0.048 (0.119) [-0.185, 0.282]			-0.035 (0.168) [-0.364, 0.294]
Observations	7970	7970	7970	7970	7970	7970
Resume Controls	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns. Marginal effects are derived from the logistic regression described in equation (3). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table 19: Estimates of Discrimination Against Applicants with Sex- and Pronoun-Based Minoritized Identities

	(D1)	(D2)	(D3)
	-0.047**	-0.089***	-0.036
Implied Male	-0.047**	-0.089***	-0.036
	[-0.088, -0.006]	[-0.131, -0.047]	[-0.101, 0.029]
	-0.003		
Implied Male × Female Dominated	-0.003		
	[-0.063, 0.057]		
	-0.109***		
Implied Female × Male Dominated	-0.109***		
	[-0.157, -0.062]		
		-0.154***	0.192
Implied Female × Percent Male		-0.154***	0.192
		[-0.222, -0.086]	[-0.162, 0.547]
			-0.344*
Implied Female × Percent Male^2			-0.344*
			[-0.702, 0.014]
	-0.054***	-0.054***	-0.054***
Nonbinary Pronouns	-0.054***	-0.054***	-0.054***
	[-0.071, -0.038]	[-0.071, -0.037]	[-0.072, -0.036]
	-0.017	-0.017	-0.017
Binary Pronouns	-0.017	-0.017	-0.017
	[-0.040, 0.005]	[-0.039, 0.005]	[-0.040, 0.005]
Observations	7970	7970	7970
Resume Controls	✓	✓	✓
Firm Controls	✓	✓	✓

Note: This table reports average marginal effects associated with implied sex disclosing pronouns compared to not disclosing pronouns. Marginal effects are derived from the logistic regression described in equation (5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table 20: Heteroskedastic Logistic Discrimination Estimates (Neumark's Bias Correction)

	Nonbinary Pronouns	Binary Pronouns
Panel A: Logistic coefficient estimates		
Coefficient Estimate	-0.054***	-0.017
	(0.008)	(0.011)
Panel B: Heteroskedastic logistic coefficient estimates		
Total Estimate	-0.056***	-0.016
	(0.008)	(0.013)
Levels Estimate	-0.053**	-0.032
	(0.021)	(0.034)
Variance Estimate	-0.004	0.016
	(0.020)	(0.034)
Panel C: Tests		
Overidentification test p-value (X_i coefficient ratios are equal for treatment and control)	0.960	0.917
Standard deviation of unobservables (treatment / control)	0.981	1.086
S.D. test p-value (ratio of standard deviations = 1)	0.881	0.654
Observations	7970	7970
Resume Controls	✓	✓
Firm Controls		

Note: This table reports average marginal effects associated with disclosing nonbinary "they/them" pronouns and binary "he/him" or "she/her" pronouns congruent with name-implied sex, compared to not disclosing pronouns. Panel A is derived from logistic regression described in equation (1) with resume controls; Panel B is derived from a heteroskedastic version of the same logistic regression and decomposed as described in equation (5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the firm level for all regressions, and reported in parentheses. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.