

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

Taryn Eames*

updated April 7, 2024

Abstract

Nonbinary people have a gender identity that falls outside the male-female binary. To investigate hiring discrimination against this group, 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. Hence, discrimination is estimated against nonbinary and presumed cisgender applicants who disclose pronouns. Results show that 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. By comparison, results are inconclusive regarding discrimination against presumed cisgender applicants who disclose pronouns; if discrimination does exist, it is of lower magnitude than discrimination against nonbinary applicants who disclose pronouns.

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 Andr s Tilcsik for helpful advice. This randomized control trial (RCT) was registered as AEARCT Trial #11183 (Eames 2023); this includes the study’s pre-analysis plan and populated pre-analysis plan (following Duflo et al. 2020). 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 and the workplace. In the labor market, job seekers now have the option to include pronouns on resumes—and many are choosing to do so. A 2022 Resume Builder survey finds that when asked 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 is especially true when disclosure reveals a minoritized 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.

To motivate this research, 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 experience 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. 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 is consistent with Coffman et al. (2024) who find that nonbinary people report experiencing discrimination across a range of outcomes and that anti-nonbinary sentiment is stronger than anti-LGBT sentiment. This provides suggestive evidence for discrimination as a driver of worse economic outcomes for nonbinary people. Hence, there is suggestive evidence that discrimination may be a 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 studies focused on hiring discrimination against the LGBT community, and gender-diverse populations in particular. Correspondence studies have been used to investigate discrimination against transgender men and women in the labor market (Bardales 2013; Rainey et al. 2017; Granberg et al. 2020) and in other contexts (Fumarco et al. 2023; Jansson and Fritzson 2022; Levy et al. 2017). In general, these studies find evidence of discrimination against transgender applicants. 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. 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 disclosing gender-typical (“he/him” or “she/her”) and gender-neutral (“they/them”) pronouns are associated with small contact penalties (below 2 percentage points) with limited statistical significance. 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. Applications were sent to 180 remote, entry-level business positions requiring an undergraduate degree and applicants who did not list pronouns 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: very large companies may have different hiring practices than other kinds of companies. Indeed, Kline et al. (2022) find that companies with more centralized hiring practices exhibit less discrimination, potentially because they may rely more on rules than on individual discretion. Further, Application Tracking Systems (ATS) have become a common hiring tool, but their use varies drastically among companies of different sizes. While 99% of Fortune 500 companies use ATS, this is true for 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 it in a central database (Find-Ernest 2023). This may not matter for identity signals communicated through name, but it does matter for identity signals communicated via pronoun disclosure on a resume PDF:

pronouns do not appear to be extracted by ATS.¹ As such, unless the hiring manager opens an applicant’s formatted resume, pronouns may not be communicated and no discrimination can occur. The external validity of Kline et al. (2022) may thus 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 in and of itself. Sentiment is also split along political lines: a 2022 YouGov poll finds that 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 list pronouns on their resume (regardless of gender identity).

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

¹To investigate this, I randomly selected 15 Fortune 500 companies, and began the application process using a resume PDF with pronouns listed below the applicant’s name. Every time the employer “auto-filled” applicant information using the resume, pronouns were not extracted.

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) find that sexual orientation wage gaps in Canada vary geographically and are largest in non-metropolitan areas. In the U.S., Tilcsik (2011) finds between-state heterogeneity in discrimination faced by openly gay men which appears to reflect local attitudes or antidiscrimination laws (or both). This study builds on existing literature 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 the 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. 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 (2020) 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. Further, I investigate whether discrimination is heightened in male- or female-dominated occupations. This is motivated by Granberg et al. (2020), who find robust evidence of discrimination against transgender men and women in male-dominated and

female-dominated occupations only.

I find that on average, disclosing “they/them” pronouns reduces positive employer response by 5.4 percentage points compared to applicants who do not disclose pronouns. Compared to presumed cisgender applicants who disclose “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. For presumed cisgender applicants who disclose pronouns, results are inconclusive: it is unclear whether these applicants experience no discrimination or some negative discrimination.

This paper is structured as follows. In Section 1.1, 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

A detailed description of the resume construction process is provided in the Appendix. This includes the randomization process, how resume inputs were sourced, formatted resume examples, and additional details on information included here.

1.1 Resume Construction

Using a resume audit study design, a resume pair was constructed for each job posting by randomizing across characteristics including education, work experience, and listed skills. Paired resumes were “matched” across several characteristics (same education level, same name-implied sex, same years of “relevant” work experience)² while remaining different enough to realistically represent two distinct applicants. In each resume pair, one was randomly assigned treatment pronouns and the other had no pronouns listed. Because I am most interested in identifying discrimination against applicants who disclose “they/them” pronouns, treated resumes have a two-thirds probability of listing these pronouns rather than “he/him” or “she/her” pronouns congruent with name-implied sex.

²If an applicant has prior work experience in the same occupation, they are considered to have “relevant” work experience. For example, when applying for a janitor role, an applicant has relevant experience if they have janitorial experience.

In generating applicant names, first names were randomly selected from the most common male and female first names in the U.S. that are not extreme in their warmth and competency scores (U.S. Social Security 2023; Newman et al. 2018). Last names were randomly selected from the most common surnames in the U.S. that are not extreme in their racial signals (U.S. Census Bureau 2021). Overall, names are largely white but not strongly so: rather than being a strong indicator of race, names are 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. Table 1 reports applicant names and emails.

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 involvement in an LGBT organization (Tilcsik 2011; Bardales 2013; Mishel 2016; Flage 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. While there is no guarantee employers will interpret binary pronoun disclosure this way, it is a reasonable expectation. 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.”

1.2 Geography Selection

Core Based Statistical Areas (CBSAs) chosen for resume distribution are described in Table 2. Geographies were selected to include pairs of CBSAs that met three criteria. First, 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.³ 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 (using 2020 Republican Presidential vote share). Note that Republican Presidential vote share is very stable over time in relative terms: from 2000 to 2020, across all six geographies, Republican CBSAs had a Republican vote share at least 15 percentage points higher than Democratic CBSAs. 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 3. 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

³Note in *Bostock vs Clayton County, Georgia* the U.S. Supreme Court interpreted protection from employment discrimination on the basis of “sex” to include sexual orientation and gender identity. However, there is no federal law or statute that explicitly protects these groups against discrimination (Minkin and Brown nd). Some states additionally explicitly prohibit employment discrimination on this basis within their own state statutes (Movement Advancement Project 2023).

are male, the occupation is deemed male-dominated (and vice-versa). 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, which influences external validity. This was done for a few 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. However, its applicability to higher-skill occupations is limited due to potentially different 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. RAs read each job posting to ensure the job being applied for was categorized appropriately, 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 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 was for a distinctly different occupation, and the first and second paired applications were 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. Finally, if job postings did not require a resume, this rendered the job posting ineligible. If no resume is required, or if applicants duplicate their resume in the application, it is unlikely that employers will open and review resume PDFs and no pronoun signal would be communicated.

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. Per Eames (2023), “employer response [is] viewed as ‘positive’ if they contact the applicant and either offer an interview or request the applicant contact them.” This excludes responses that confirm application submission, invite applicants to fill out an additional application on another portal, notify the applicant that the job was filled, and questions

like “Are you still interested in the position?” which are ambiguous and may be sent to all applicants.

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) a populated pre-analysis plan (where that plan is rigorously followed and all discussed analyses are presented) is available in Trial #11183 documents. The empirical strategy employed here is very similar, and despite small methodology tweaks, results are nearly identical.

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

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

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 job posting characteristics which may 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) . Estimates $\hat{\gamma}, \hat{\lambda}$ can be interpreted as discrimination against applicants who disclose pronouns.

Resume characteristics in vector X_i include fixed effects (occupation, location, and RA), timing variables (which resume was sent first, lag length between first and second application), indicator variables for education level and listed skills, and work experience-related variables (years and timing of relevant and common work experiences). Job posting characteristics in vector Z_j include the same fixed effects, estimated application volume, and measures of posted wage relative to the occupation average. Detailed descriptions of all control variables are available in Tables 4 and 5.

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:

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

Since all applicants disclose pronouns in this regression, δ represents additional discrimination 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:

$$(3) \quad \xi = \delta/\gamma$$

The remaining discrimination can be attributed to the act of pronoun disclosure (which presumed cisgender applicants also face).

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

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

where I is a vector of interaction variables described in Table 6. In general, interactions are indicator variables; where possible, an alternative version of regression (4) is investigated which replaces indicator variables with continuous variables.

3 Results

3.1 Summary Statistics

Figure 1 shows positive employer response rates by pronoun disclosure group; Figure 2 shows the same thing, comparing Republican to Democratic geographies. Table 7 shows the raw differences in positive response rates by pronoun disclosure, both in total and by group of interest (implied sex, state, geographic politics, occupation categorization). For each difference in response between treatment and control groups, Chi-squared test results are also reported. Table 8 shows the same information by individual occupation.

It can be seen that 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 geographies with different politics are large. 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

Table 9 reports regression results for equation (1). Estimates are very similar across specification (unsurprising given that resumes are randomized); the preferred specification is

(D) which includes both resume and job posting controls. In this specification, disclosing nonbinary “they/them” pronouns changes the rate of positive employer response by -5.4 percentage points relative to no pronoun disclosure on average. This estimate is statistically significant at the 0.1% level with a 95% confidence interval of -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 positive discrimination can be effectively ruled out, results are inconclusive regarding whether these applicants experience no discrimination or some negative discrimination.

Table 10 reports regression results for equation (2) and shows that applicants who disclose “they/them” pronouns face more discrimination than 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 these tables, from equation (3) I estimate that 67% of discrimination faced by applicants who disclose “they/them” pronouns is gender identity-based; however, this estimate is imprecise. More clear is that nonbinary applicants face more discrimination than presumed cisgender applicants who disclose pronouns.

3.3 Secondary Hypotheses

Table 11 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 (0.9 to 7.5 percentage points)—approximately 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 Republican vote share. Note that while CBSAs are generally stable over time in terms of relative Republican vote share, actual vote share fluctuates with each election. Hence, while this is a useful check, results associated with Republican geography indicators are likely more insightful. 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 control for state-level macroeconomic factors and legislation.

Further, two of the three geographic pairs are neighboring, increasing their environmental similarities. However, it may be something else: perhaps geographic politics are correlated with other factors that are leading to differences in discrimination. For example, Table 12 reports differences in county-level averages between Republican and Democratic CBSAs across a range of variables. In Democratic CBSAs, county-level population, population density, median household income, and education levels are higher; percent white and number of religious congregations per 100K are smaller. These trends hold for the geographies in this study’s research sample.

Table 13 reports the results of equation (4) including all interactions. Results are consistent with Table 11, but also show inconclusive results for other secondary hypotheses. Unsurprising given limited power, I am unable to conclude whether implied sex or occupation characteristics are associated with more or less discrimination.

3.4 Robustness Checks and Other Analyses

I conduct a variety of robustness checks and some additional analyses, with details and results reported in the Appendix.

I address the Heckman-Siegelman critique using the method described in Neumark (2012).⁴ Results are consistent with those presented here. In addition, I produce Tables 9 to 13 with a host of modifications. First, I use a linear probability model in place of a logistic model—results are close to identical. I also use two alternative definitions of positive employer response. One alternative 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.

To test for statistical discrimination, I interact years of relevant work experience with pronoun disclosure (following Granberg et al. 2020). Results are inconclusive regarding the extent to which work experience influences employer response. To contextualize estimates and consider intersectionality, I compare 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 nonbinary discrimination is similar in magnitude to discrimination faced by these groups and that applicants with multiple minoritized identities are doubly disadvantaged. Finally, I show additional regression results associated with resume controls for equation (1)—in particular, how more years of relevant work experience increases

⁴Heckman and Siegelman (1993) and Heckman (1998) present a critique of audit studies and show that if there is a difference in the variance of unobserved productivity determinants between groups, this can bias discrimination estimates.

positive employer response. The reduction in positive employer response faced by nonbinary applicants who disclose pronouns is similar in magnitude to an applicant going from having one year of relevant work experience to zero years of relevant work experience.

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 are 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: I find that doing so reduces positive employer response by 5.4 percentage points. Since the average positive employer response rate for the control group is 31.3%, this represents a reduction of 17%. 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 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. Not only is their point estimate outside the 95% confidence interval found here (-7.1 to -3.8 percentage points), but the lower bound of their confidence interval is too (-3.4 percentage points). This suggests that there may be important differences in hiring practices between very large companies and smaller companies resulting in disparate rates of discrimination at the initial application stage. One potential driver is the use of ATS which is much more common among Fortune 500 companies and may

blind pronoun disclosure by default. Hiring centralization may also play a role: Kline et al. (2022) find that companies with more centralized hiring practices exhibit less discrimination, potentially because they may rely more on rules than on individual discretion. Of course, it is worth considering the extent to which lower discrimination at this stage of the hiring process translates into differences in discrimination when it comes to job offers. Rather than reflecting actual differences in hiring discrimination, very large companies may simply postpone discrimination to the next phase of the hiring process.

Considering how discrimination varies geographically, I find that discrimination against applicants who disclose “they/them” pronouns is approximately double in Republican than in Democratic geographies: positive employer response is reduced by 3.5 percentage points (11%) and 7.5 percentage points (25%) respectively. By controlling for state-level economic environments and legislation, differences in geographic politics may be driven by attitudinal differences—especially since survey results indicate political divides in sentiment toward transgender people and gender-neutral pronouns (Parker et al. 2022; Ballard 2022). That being said, differences may also or instead be driven by factors that 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 Robustness Checks and Other Analyses above), taste-based discrimination is a much more likely source. Consider that the vast majority of Americans are not commonly in contact with people who use 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). Hence, it would be impossible for these people to form accurate statistical priors about this group that are not wholly informed by stereotypes or preferences. 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 priors.

This study shows that there is meaningful discrimination against applicants who disclose “they/them” pronouns during the hiring process. This motivates additional research which may seek to understand mechanisms and potential mitigating factors. What information is conveyed to employers when applicants disclose pronouns? Does new hiring technology mitigate (or exacerbate) discrimination? How can bias, unconscious or otherwise, be combated? As more data sources begin including information about gender identity, additional investigation is possible.

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.
- Bardales, N. (2013). Finding a job in “ a beard and a dress ” : Evaluating the effectiveness of transgender anti-discrimination laws .
- 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.

- Coffman, K. B., Coffman, L. C., and Ericson, K. M. (2024). Non-binary gender economics. Working Paper 32222, National Bureau of Economic Research.
- 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. (2020). Discrimination against gays and lesbians in hiring decisions: A meta-analysis. *International Journal of Manpower*, 41(6):671–691.
- Fumarco, L., Harrell, B., Patrick, B., David, S., and Dils, E. (2023). Gender identity, race, and ethnicity-based discrimination in access to mental health care: Evidence from an audit correspondence field experiment. *MUNI ECON Working Papers*.
- 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.
- Jansson, J. and Fritzson, S. (2022). Gender and gender identity in the rental housing market: Evidence from a correspondence study. *SSRN Working Paper*.
- 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.
- Levy, D. K., Wissoker, D., Aranda, C. L., Howell, B., Pitingolo, R., Sewell, S., and Santos, R. (2017). A paired-testing pilot study of housing discrimination against same-sex couples and transgender individuals. Urban Institute. https://www.urban.org/sites/default/files/publication/91486/2017.06.27_hds_lgt_final_report_report_finalized.pdf. Accessed March 15, 2024.
- 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.
- Mishel, E. (2016). Discrimination against queer women in the u.s. workforce: A résumé audit study. *Socius*, 2:2378023115621316.
- 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.
- Neumark, D. and Rich, J. (2019). Do field experiments on labor and housing markets overstate discrimination? A re-examination of the evidence. *ILR Review*, 72(1):223–252.
- 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.
- Rainey, T., Imse, E. E., and Pomerantz, A. (2017). Qualified and transgender: A report on results of resume testing for employment discrimination based on gender identity. Office of Human Rights, District of Columbia. https://ohr.dc.gov/sites/default/files/dc/sites/ohr/publication/attachments/QualifiedAndTransgender_FullReport_1.pdf. Accessed March 15, 2024.
- 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/vol11/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

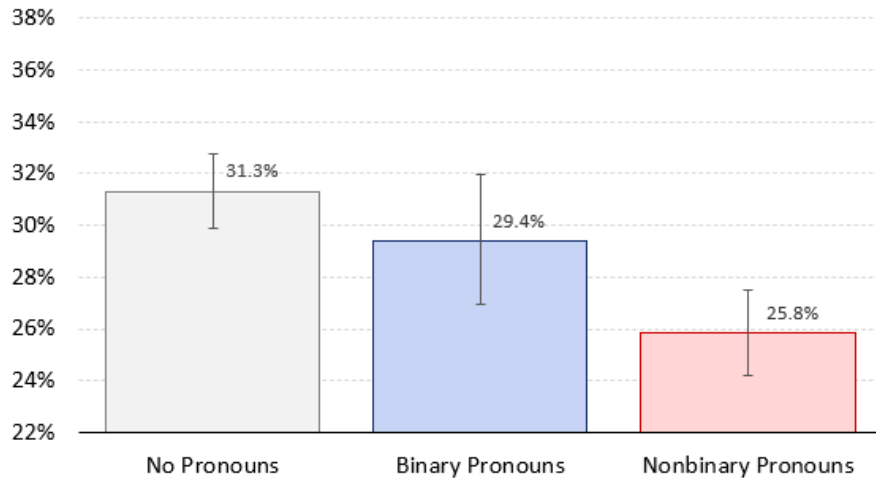


Figure 1: Positive Employer Response by Pronoun Disclosure

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.

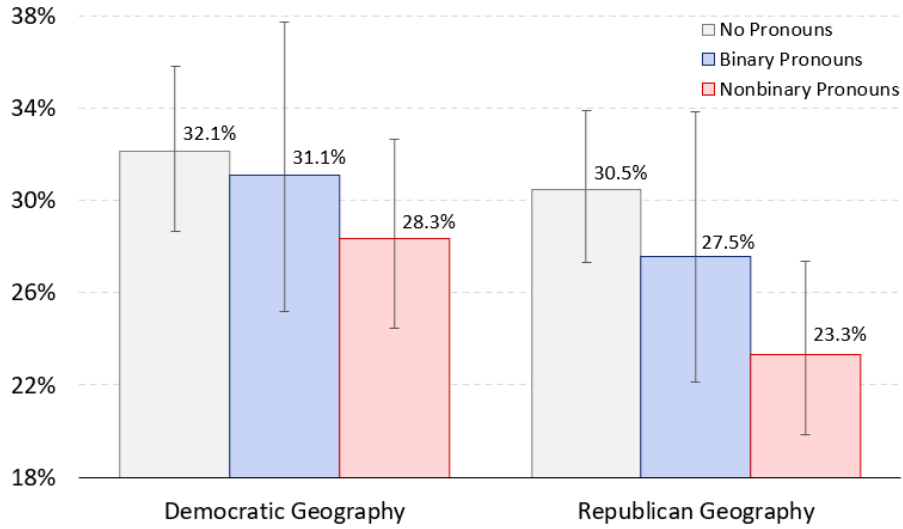


Figure 2: Positive Employer Response Rates by Pronoun Disclosure and Geographic Politics

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.

Tables

Table 1: 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. In addition, 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: Geographies

CBSA	Population		Adjusted Republican Presidential Vote Share (%)						Category
	Count	Density	2000	2004	2008	2012	2016	2020	
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 count is listed in thousands and sourced from 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 3: 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 (CensusBureau2022A). 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 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. Occupations with scores above 75 are deemed high customer-facing, between 50 and 75 medium, and below 50 low.

Table 4: 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 A1.6 in the Appendix: 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 5: Job Posting 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 6: Interaction Variables

Variable	Description
<i>Panel A: Indicator variables</i>	
Republican Geography	Equals 1 if the job is located in a Republican geography (Spokane, WA; Provo, UT; Colorado Springs, CO).
Implied Male	Equals 1 if the applicant is implied to be male (through name assignment).
Male-Dominated	Equals 1 if the applicant is applying in a male-dominated occupation (construction worker, truck driver, warehouse worker, janitor, landscaper).
Female-Dominated	Equals 1 if the applicant is applying in a female-dominated occupation (receptionist, cashier, housekeeper, certified nursing assistant, administrative assistant).
High Customer-Facing	Equals 1 if the applicant is applying in a high customer interaction occupation (receptionist, cashier, retail salesperson, server).
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).
<i>Panel B: Continuous replacements</i>	
Republican Vote Share	Replaces Republican. Equals the Republican vote share in a CBSA, adjusted such that Republican and Democratic vote shares sum to 1.
Republican Vote Share ²	Replaces Republican. Above squared.
Percent Male	Replaces Male-Dominated and Female-Dominated. Equals the percent of the workforce in the occupation who is male.
Percent Male ²	Replaces Male-Dominated and Female-Dominated. Above squared.
O*NET Score	Replaces High Customer-Facing and Low Customer-Facing. 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.
O*NET Score ²	Replaces High Customer-Facing and Low Customer-Facing. Above squared.

Table 7: Differences in Positive Employer Response by Group

Observations	Positive Employer Response					Sample Size		
	NP	NB	NB - NP	B	B - NP	NP	NB	B
All Observations	0.313	0.258	-0.055 *** (0.011)	0.294	-0.019 (0.015)	3985	2695	1290
Implied Males	0.307	0.253	-0.053 *** (0.016)	0.291	-0.016 (0.021)	1994	1365	629
Implied Females	0.319	0.263	-0.056 *** (0.016)	0.297	-0.022 (0.021)	1991	1330	661
Washington	0.307	0.251	-0.056 *** (0.020)	0.286	-0.021 (0.026)	1323	910	413
Colorado	0.316	0.259	-0.058 *** (0.020)	0.296	-0.021 (0.026)	1325	882	443
Utah	0.316	0.266	-0.050 ** (0.020)	0.30	-0.016 (0.026)	1337	903	434
Democratic City	0.321	0.283	-0.038 ** (0.016)	0.311	-0.010 (0.021)	1999	1337	662
Republican City	0.305	0.233	-0.071 *** (0.016)	0.275	-0.029 (0.021)	1986	1358	628
Male-Dominated	0.289	0.235	-0.054 *** (0.019)	0.277	-0.011 (0.025)	1376	932	444
Non-Dominated	0.330	0.265	-0.065 *** (0.020)	0.299	-0.031 (0.026)	1305	864	441
Female-Dominated	0.321	0.276	-0.045 ** (0.020)	0.306	-0.015 (0.027)	1304	899	405
High Customer Facing	0.304	0.244	-0.059 *** (0.021)	0.284	-0.020 (0.028)	1176	806	370
Medium Customer Facing	0.293	0.260	-0.034 (0.021)	0.265	-0.028 (0.027)	1186	786	400
Low Customer Facing	0.334	0.267	-0.066 *** (0.018)	0.323	-0.011 (0.024)	1623	1103	520

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. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table 8: Differences in Positive Employer Response by Occupation

Observations	Positive Employer Response					Sample Size		
	NP	NB	NB - NP	B	B - NP	NP	NB	B
Administrative Assistant	0.161	0.116	-0.045 (0.039)	0.197	0.037 (0.058)	218	147	71
Construction Worker	0.181	0.163	-0.018 (0.044)	0.189	0.008 (0.057)	215	141	74
Receptionist	0.221	0.199	-0.022 (0.039)	0.204	-0.017 (0.051)	299	201	98
Server	0.265	0.197	-0.068 (0.050)	0.250	-0.015 (0.066)	200	132	68
Janitor	0.286	0.228	-0.057 (0.048)	0.345	0.060 (0.077)	217	162	55
Assembler	0.295	0.248	-0.048 (0.059)	0.246	-0.049 (0.071)	166	105	61
Landscaper	0.310	0.234	-0.075 (0.050)	0.294	-0.016 (0.069)	213	145	68
Truck Driver	0.313	0.262	-0.051 (0.037)	0.279	-0.034 (0.048)	396	267	129
Warehouse Worker	0.316	0.253	-0.063 (0.041)	0.288	-0.028 (0.052)	335	217	118
Housekeeper	0.319	0.298	-0.021 (0.051)	0.295	-0.024 (0.064)	229	151	78
Cook	0.324	0.291	-0.033 (0.041)	0.277	-0.046 (0.051)	346	227	119
Retail Sales	0.348	0.263	-0.085 ** (0.033)	0.319	-0.029 (0.044)	500	334	166
Cashier	0.362	0.309	-0.052 (0.057)	0.395	0.033 (0.095)	177	139	38
Baker	0.462	0.348	-0.114 (0.085)	0.519	0.056 (0.121)	93	66	27
Certified Nursing Assistant	0.475	0.395	-0.080 * (0.041)	0.433	-0.042 (0.055)	381	261	120

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. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table 9: Estimates of Discrimination Against Applicants who Disclose Pronouns

	(A)	(B)	(C)	(D)
Nonbinary Pronouns	-0.054*** (0.008) [-0.070, -0.039]	-0.054*** (0.008) [-0.071, -0.038]	-0.055*** (0.008) [-0.070, -0.040]	-0.054*** (0.008) [-0.071, -0.038]
Binary Pronouns	-0.018 (0.012) [-0.041, 0.004]	-0.017 (0.012) [-0.039, 0.006]	-0.016 (0.011) [-0.039, 0.006]	-0.017 (0.011) [-0.039, 0.006]
Observations	7970	7970	7970	7970
Resume Controls		✓		✓
Job Controls			✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns derived from the logistic regression described in equation (1). 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 10: Estimates of Gender Identity-Based Discrimination Against Nonbinary Applicants who Disclose Pronouns

	(A)	(B)	(C)	(D)
Nonbinary Pronouns	-0.036** (0.015) [-0.065, -0.006]	-0.036** (0.015) [-0.066, -0.007]	-0.038*** (0.014) [-0.066, -0.010]	-0.037** (0.015) [-0.066, -0.008]
Observations	3985	3985	3985	3985
Resume Controls		✓		✓
Job Controls			✓	✓

Note: This table 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 derived from the logistic regression described in equation (2); only treated observations are included. 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 11: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Geographic Politics

	Nonbinary Pronouns		Binary Pronouns	
	(D1)	(D2)	(D1)	(D2)
Pronouns	-0.035*** (0.011) [-0.057, -0.014]	0.197* (0.108) [-0.015, 0.409]	-0.010 (0.016) [-0.041, 0.021]	0.080 (0.183) [-0.280, 0.439]
Pronouns \times Republican	-0.040** (0.016) [-0.071, -0.009]		-0.013 (0.023) [-0.058, 0.032]	
Pronouns \times Vote Share		-0.949** (0.465) [-1.861, -0.038]		-0.366 (0.694) [-1.727, 0.994]
Pronouns \times Vote Share ²		0.827* (0.451) [-0.057, 1.711]		0.334 (0.671) [-0.981, 1.649]
Observations	7970	7970	7970	7970
Resume Controls	✓	✓	✓	✓
Job Controls	✓	✓	✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns 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 12: County Differences in Democratic and Republican CBSAs

Variable	County-Level Mean		
	Democratic CBSA	Republican CBSA	Difference
<i>Panel A: Counties in all U.S. CBSAs</i>			
Population (1,000s)	332.3	88.8	243.4 *** (42.2)
Population Density	1058	165	893 *** (247)
Median Household Income (\$1,000s)	73.1	58.5	14.6 *** (1.3)
Education: Percent Less High School	0.102	0.118	-0.016 *** (0.006)
Education: Percent Bachelor's or More	0.325	0.226	0.099 *** (0.014)
Percent White	0.765	0.861	-0.096 *** (0.012)
Percent Black	0.151	0.083	0.068 *** (0.011)
Percent Other	0.084	0.056	0.028 *** (0.005)
Religious Congregations per 100K	127	196	-69.4 *** (12.35)
<i>Panel B: Counties in the six study CBSAs</i>			
Population (1,000s)	552.4	298.9	253.5 (219.2)
Population Density	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 standard errors associated with a t-test are also reported. 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 Department of Agriculture (2023), and religious congregation data from US Religious Census (2020). Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table 13: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions

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

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns derived from the logistic regression described in equation (4). 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.

Appendix

A1 Resume Construction

A1.1 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: 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.
- Name: resumes are assigned a name, and are matched same in terms of implied sex

but matched different in terms of specific name.

- **Summary:** 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:** 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:** 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:** 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 A.7) which additionally determines the phone number, resume format (Section A1.7), and order applications are sent in. Names are randomly assigned and independent from the above.

A1.2 Pronoun Treatment

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 (Mishel 2016; Tilcsik 2011; Flage 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) find 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.”

A1.3 Name

The first names used in this study, where some imply the applicant is male and others female, are provided in Table A14. 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 A15. 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.

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 1. 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).

A1.4 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 A1.1 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).

A1.5 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.⁵ 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.

A1.6 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 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

⁵In 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

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 occupation⁶. 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 resumes for workers living in Idaho who currently hold that position.⁷ 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.

A1.7 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

⁶In cases where there did not exist 150 resumes of people currently holding that occupation in the geography of interest, all available data was scraped

⁷A 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).

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 Fig. A1 and Fig. A2.

A2 Robustness Checks and Other Analyses

A2.1 Addressing the Heckman-Siegelman Critique

Heckman and Siegelman show that if the variance of unobservable determinants of productivity differs between treatment and control groups, correspondence studies can find spurious estimates of discrimination (Heckman and Siegelman 1993; Heckman 1998). That is, if employers engage in second-moment statistical discrimination, correspondence study estimates can be biased in either direction. This is true even if correspondence studies keep observable productivity indicators experimentally constant.

Neumark developed a method to address this critique which relies on an additional identifying assumption: some applicant characteristics affect perceived productivity and their impact does not vary between groups (Neumark 2012). Under this assumption (with testable implications), discrimination estimates can be disaggregated into a level part that includes taste-based and first-moment statistical discrimination, and a variance part that includes second-moment statistical discrimination. This adjustment can meaningfully change results: when re-assessing evidence from six resume studies that find evidence of labor market discrimination with sufficient information to correct for this bias, Neumark and Rich (2019) find that unbiased (level) estimates for half of them decrease to near zero, become statistically insignificant, or change sign.

I use this method (via heteroskedastic logistic regression) and results are presented in Table A16; I referenced code from Neumark et al. (2016) when generating. Using this method, the unbiased discrimination estimate against applicants who disclose “they/them” pronouns is 5.3 percentage points and statistically significant at the 5% level; there is no evidence that the identifying assumption is violated. Estimated discrimination against applicants who disclose “he/him” or “she/her” pronouns remains statistically insignificant.

A2.2 Linear Probability Model

As a robustness check, I run the following linear probability models using the same notation as described in the main text (in place of logistic regression):

$$(1)' \quad y_{ij} = \alpha + \gamma NB_i + \lambda B_i + X_i' \beta_1 + Z_j' \beta_2 + \varepsilon_{ij}$$

$$(2)' \quad y_{ij} = \alpha + \delta NB_i + X_i' \beta_1 + Z_j' \beta_2 + \varepsilon_{ij}$$

$$(4)' \quad y_{ij} = \alpha + \gamma_1 NB_i + \gamma_2 [NB_i \cdot I] + \lambda_1 B_i + \lambda_2 [B_i \cdot I] + X_i' \beta_1 + Z_j' \beta_2 + \varepsilon_{ij}$$

where y_{ij} equals 1 if applicant i received a positive response from job posting j .

Results are reported in tables A17 to A20, and are nearly identical to what is reported in the main tables.

A2.3 Alternative Positive Employer Response: More Strict

Per Eames (2023), “employer response [is] viewed as ‘positive’ if they contact the applicant and either offer an interview or request the applicant contact them.” I consider an alternative definition that is more strict: employer responses is only considered positive if the applicant is offered an interview. Compared to the main definition where positive employer response is 31.3% for the control group, positive employer response is 25.1% in this more strict alternative.

Results are reported in tables A21 to A24. Overall, results are consistent with what is reported in the main tables, though more nonbinary discrimination is estimated to be driven by gender identity rather than the act of pronoun disclosure more generally (88%).

A2.4 Alternative Positive Employer Response: Less Strict

Per Eames (2023), “employer response [is] viewed as ‘positive’ if they contact the applicant and either offer an interview or request the applicant contact them.” I consider an alternative definition that is less strict: employer responses is considered positive if there is any possibility the response could be viewed as positive. Compared to the main 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. Compared to the main definition where positive employer response is 31.3% for the control group, positive employer response is 34.7% in this less strict alternative.

Results are reported in tables A25 to A28. Overall, results are consistent with what is reported in the main tables.

A2.5 Statistical Discrimination

To test for statistical discrimination, I interact years of relevant work experience with pronoun disclosure (following Granberg et al. 2020). To do this, I run the following regression:

$$(5) \quad p_{ij} = (1 + \exp(\alpha + \gamma NB_i + \lambda B_i + \eta_1 RE_i + \eta_2[NB_i \cdot RE_i] + \eta_3[NB_i \cdot RE_i^2] + \eta_4[B_i \cdot RE_i] + \eta_5[B_i \cdot RE_i^2] + X_i'\beta_1 + Z_j'\beta_2 + \varepsilon_{ij}))^{-1}$$

Note that if an applicant has prior work experience in the same occupation, they are considered to have “relevant” work experience. For example, when applying for a janitor role, an applicant has relevant experience if they have janitorial experience. The rationale behind this approach is that the more years of relevant experience an applicant has, the less employers need to rely on statistical priors. Hence, if discrimination magnitude decreases as years of relevant experience increases, this is evidence of statistical discrimination.

Table A29 reports results from equation (5) and shows that there is inconclusive evidence regarding whether discrimination magnitude for applicants who disclose nonbinary pronouns and for presumed cisgender applicants who disclose binary pronouns.

A2.6 Discrimination Comparison

A2.6.1 Compare to Another Discriminated Group

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. 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.

To do this, I run the following logistic regression:

$$(6) \quad p_{ij} = (1 + \exp(\alpha + \gamma NB_i + \lambda B_i + \eta_1 M_i + \eta_2[M_i \cdot FD_j] + \eta_3[F_i \cdot MD_j] + X_i'\beta_1 + Z_j'\beta_2 + \varepsilon_{ij}))^{-1}$$

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.

Table A30 reports results from equation (6) 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 monitized 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 Fig. A3.

A2.6.2 Compare to an Applicant with Less Relevant Work Experience

Table A31 reports the results of equation (1) including both what was shown in Table 9 and additionally including select X_i control variables. This table shows that going from one to zero years of relevant experience decreases positive employer response by an estimated 4.7 percentage points (2.4 percentage points when going from two to one year). Similarly, moving relevant experience from the most recent year to an earlier experience reduces positive employer response by 4.8 percentage points. Hence, discrimination against applicants who disclose nonbinary “they/them” pronouns is similar in magnitude to an applicant going from one to zero years of relevant experience, or an applicant moving their relevant experience farther back in their resume—from their current experience to a historic experience.

Appendix Figures

Parker Reed

they/them

Location: Denver, CO

reed.parker@outlook.com | 1-720-316-7376

SUMMARY

- Organized and efficient
- Team player
- Able to put patients at ease
- Fast learner
- Computer skills (tech savvy)
- 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 A1: 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 A2: Resume Format 2 Example

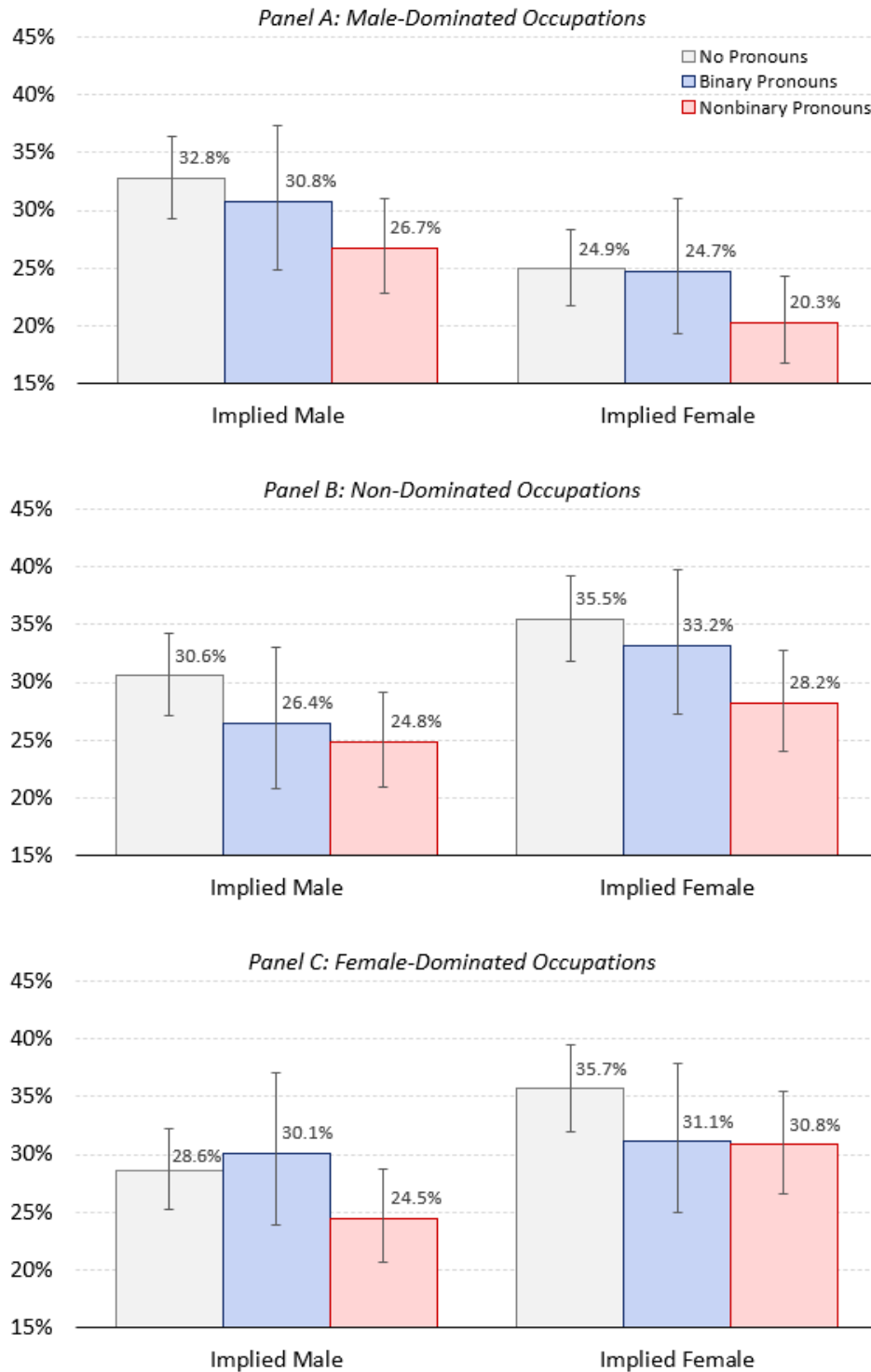


Figure A3: Positive Employer Response Rates by Pronoun Disclosure and Implied Sex
 Note: This figure reports positive employer response rates for treatment and control groups, for implied male and female applicants. Whiskers show the 95% confidence interval associated with the true positive employer response rate for each group, calculated using the normal approximation to the binomial distribution.

Appendix Tables

Table A14: First Names

Implied Sex	First Name	1990s Baby Name Popularity		Name Association Scores	
		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 A15: Last Names

Last Name	Name Popularity		Racial Composition		
	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	58.2	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 A16: Heteroskedastic Logistic Discrimination Estimates (Neu-mark’s Bias Correction)

	Nonbinary Pronouns	Binary Pronouns
<i>Panel A: Logistic coefficient estimates</i>		
Coefficient Estimate	-0.054*** (0.008)	-0.017 (0.011)
<i>Panel B: Heteroskedastic logistic coefficient estimates</i>		
Total Estimate	-0.056*** (0.008)	-0.016 (0.013)
Levels Estimate	-0.053** (0.021)	-0.032 (0.034)
Variance Estimate	-0.004 (0.020)	0.016 (0.034)
<i>Panel C: Tests</i>		
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.

Table A17: Estimates of Discrimination Against Applicants who Disclose Pronouns (Linear Probability Model)

	(A)	(B)	(C)	(D)
Nonbinary Pronouns	-0.055*** (0.008) [-0.070, -0.039]	-0.055*** (0.008) [-0.070, -0.039]	-0.056*** (0.008) [-0.071, -0.040]	-0.055*** (0.008) [-0.070, -0.039]
Binary Pronouns	-0.019 (0.012) [-0.043, 0.004]	-0.018 (0.012) [-0.041, 0.005]	-0.017 (0.012) [-0.041, 0.006]	-0.018 (0.012) [-0.041, 0.005]
Observations	7970	7970	7970	7970
Resume Controls		✓		✓
Job Controls			✓	✓

Note: This table reports the estimated impact of disclosing pronouns compared to not disclosing pronouns derived from the linear probability model described in equation (1)'. The dependent variable is an indicator variable which equals 1 if the applicant received an interview request. 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 A18: Estimates of Gender Identity-Based Discrimination Against Non-binary Applicants who Disclose Pronouns (Linear Probability Model)

	(A)	(B)	(C)	(D)
Nonbinary Pronouns	-0.036** (0.015) [-0.065, -0.006]	-0.036** (0.015) [-0.066, -0.007]	-0.038** (0.015) [-0.068, -0.009]	-0.036** (0.015) [-0.066, -0.007]
Observations	3985	3985	3985	3985
Resume Controls		✓		✓
Job Controls			✓	✓

Note: This table reports the estimated impact of disclosing nonbinary “they/them” pronouns compared to disclosing binary “he/him” or “she/her” pronouns congruent with name-implied sex derived from the linear probability model described in equation (2)'; only treated observations are included. The dependent variable is an indicator variable which equals 1 if the applicant received an interview request. 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 A19: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Geographic Politics (Linear Probability Model)

	Nonbinary Pronouns		Binary Pronouns	
	(D1)	(D2)	(D1)	(D2)
Pronouns	-0.032*** (0.010) [-0.052, -0.012]	0.232** (0.107) [0.023, 0.441]	0.000 (0.014) [-0.028, 0.028]	-0.005 (0.154) [-0.306, 0.296]
Pronouns	-0.037*** (0.011) [-0.059, -0.015]	0.164 (0.110) [-0.052, 0.380]	-0.011 (0.017) [-0.044, 0.022]	0.066 (0.175) [-0.276, 0.409]
Pronouns × Republican	-0.036** (0.016) [-0.067, -0.005]		-0.014 (0.024) [-0.061, 0.032]	
Pronouns × Vote Share		-0.819* (0.450) [-1.702, 0.064]		-0.323 (0.706) [-1.708, 1.061]
Pronouns × Vote Share ²		0.707 (0.437) [-0.150, 1.563]		0.288 (0.681) [-1.047, 1.624]
Observations	7970	7970	7970	7970
Resume Controls	✓	✓	✓	✓
Job Controls	✓	✓	✓	✓

Note: This table reports the estimated impact of disclosing pronouns compared to not disclosing pronouns derived from the linear probability model described in equation (4)' including only political interactions. The dependent variable is an indicator variable which equals 1 if the applicant received an interview request. 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 A20: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions (Linear Probability Model)

	Nonbinary Pronouns		Binary Pronouns	
	(D1)	(D2)	(D1)	(D2)
Pronouns	-0.026 (0.024) [-0.072, 0.020]	0.143 (0.135) [-0.121, 0.407]	-0.038 (0.034) [-0.105, 0.029]	0.048 (0.209) [-0.361, 0.457]
Pronouns \times Implied Male	0.005 (0.016) [-0.026, 0.036]	0.005 (0.016) [-0.026, 0.036]	0.002 (0.024) [-0.045, 0.048]	0.002 (0.024) [-0.045, 0.049]
Pronouns \times Republican	-0.036** (0.016) [-0.067, -0.005]		-0.015 (0.024) [-0.062, 0.031]	
Pronouns \times Vote Share		-0.816* (0.451) [-1.699, 0.068]		-0.319 (0.710) [-1.711, 1.073]
Pronouns \times Vote Share ²		0.705 (0.437) [-0.152, 1.561]		0.283 (0.685) [-1.060, 1.626]
Pronouns \times High Customer-Facing	-0.028 (0.023) [-0.073, 0.017]		0.028 (0.035) [-0.040, 0.096]	
Pronouns \times Low Customer-Facing	-0.039** (0.019) [-0.076, -0.001]		0.021 (0.029) [-0.035, 0.077]	
Pronouns \times O*NET Score		0.001 (0.002) [-0.004, 0.006]		0.001 (0.003) [-0.006, 0.007]
Pronouns \times O*NET Score ²		0.000 (0.000) [0.000, 0.000]		0.000 (0.000) [0.000, 0.000]
Pronouns \times Male-Dominated	0.009 (0.022) [-0.035, 0.053]		0.021 (0.033) [-0.043, 0.084]	
Pronouns \times Female-Dominated	0.024 (0.020) [-0.016, 0.064]		0.009 (0.031) [-0.051, 0.069]	
Pronouns \times Percent Male		-0.100 (0.113) [-0.321, 0.121]		0.018 (0.169) [-0.313, 0.349]
Pronouns \times Percent Male ²		0.095 (0.110) [-0.121, 0.311]		-0.024 (0.164) [-0.346, 0.297]
Observations	7970	7970	7970	7970
Resume Controls	✓	✓	✓	✓
Job Controls	✓	✓	✓	✓

Note: This table reports the estimated impact of disclosing pronouns compared to not disclosing pronouns derived from linear probability equation (4)'. The dependent variable is an indicator variable which equals 1 if the applicant received an interview request. 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 A21: Estimates of Discrimination Against Applicants who Disclose Pronouns (Alternative Positive Employer Response: Interview Request)

	(A)	(B)	(C)	(D)
<i>Panel A: Disclosing pronouns compared to not disclosing pronouns</i>				
Nonbinary Pronouns	-0.047*** (0.007) [-0.061, -0.033]	-0.047*** (0.008) [-0.063, -0.032]	-0.048*** (0.007) [-0.062, -0.034]	-0.047*** (0.008) [-0.063, -0.032]
Binary Pronouns	-0.005 (0.011) [-0.026, 0.016]	-0.005 (0.011) [-0.026, 0.016]	-0.004 (0.011) [-0.025, 0.017]	-0.005 (0.011) [-0.026, 0.016]
Observations	7970	7970	7970	7970
Resume Controls		✓		✓
Job Controls			✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns derived from the logistic regression described in equation (1). The dependent variable is an indicator variable which equals 1 if the applicant received an interview request. 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 A22: Estimates of Gender Identity-Based Discrimination Against Nonbinary Applicants who Disclose Pronouns (Alternative Positive Employer Response: Interview Request)

	(A)	(B)	(C)	(D)
Nonbinary Pronouns	-0.042*** (0.014) [-0.070, -0.014]	-0.042*** (0.014) [-0.070, -0.014]	-0.043*** (0.013) [-0.069, -0.018]	-0.042*** (0.014) [-0.070, -0.014]
Observations	3985	3985	3985	3985
Resume Controls		✓		✓
Job Controls			✓	✓

Note: This table 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 derived from the logistic regression described in equation (2); only treated observations are included. The dependent variable is an indicator variable which equals 1 if the applicant received an interview request. 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 A23: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Geographic Politics (Alternative Positive Employer Response: Interview Request)

	Nonbinary Pronouns		Binary Pronouns	
	(D1)	(D2)	(D1)	(D2)
Pronouns	-0.032*** (0.010) [-0.052, -0.012]	0.232** (0.107) [0.023, 0.441]	0.000 (0.014) [-0.028, 0.028]	-0.005 (0.154) [-0.306, 0.296]
Pronouns × Republican	-0.032** (0.015) [-0.061, -0.004]		-0.009 (0.021) [-0.051, 0.032]	
Pronouns × Vote Share		-1.053** (0.436) [-1.907, -0.198]		0.028 (0.633) [-1.212, 1.268]
Pronouns × Vote Share ²		0.944** (0.421) [0.118, 1.770]		-0.054 (0.612) [-1.253, 1.145]
Observations	7970	7970	7970	7970
Resume Controls	✓	✓	✓	✓
Job Controls	✓	✓	✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns 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 an interview request. 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 A24: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions (Alternative Positive Employer Response: Interview Request)

	Nonbinary Pronouns		Binary Pronouns	
	(D1)	(D2)	(D1)	(D2)
Pronouns	-0.011 (0.021) [-0.052, 0.031]	0.193 (0.134) [-0.070, 0.455]	-0.030 (0.028) [-0.085, 0.025]	-0.013 (0.184) [-0.373, 0.348]
Pronouns × Implied Male	-0.008 (0.015) [-0.037, 0.021]	-0.008 (0.015) [-0.037, 0.021]	0.000 (0.021) [-0.042, 0.042]	0.000 (0.021) [-0.042, 0.042]
Pronouns × Republican	-0.032** (0.015) [-0.061, -0.004]		-0.011 (0.021) [-0.052, 0.030]	
Pronouns × Vote Share		-1.053** (0.438) [-1.911, -0.196]		0.030 (0.637) [-1.219, 1.278]
Pronouns × Vote Share ²		0.946** (0.423) [0.116, 1.775]		-0.058 (0.616) [-1.265, 1.148]
Pronouns × High Customer-Facing	-0.031 (0.020) [-0.071, 0.008]		0.026 (0.033) [-0.038, 0.090]	
Pronouns × Low Customer-Facing	-0.030* (0.018) [-0.065, 0.006]		0.022 (0.027) [-0.032, 0.075]	
Pronouns × O*NET Score		0.002 (0.002) [-0.003, 0.007]		0.001 (0.003) [-0.005, 0.006]
Pronouns × O*NET Score ²		0.000 (0.000) [0.000, 0.000]		0.000 (0.000) [0.000, 0.000]
Pronouns × Male-Dominated	-0.007 (0.021) [-0.048, 0.034]		0.026 (0.032) [-0.036, 0.088]	
Pronouns × Female-Dominated	0.021 (0.020) [-0.018, 0.059]		0.022 (0.029) [-0.035, 0.078]	
Pronouns × Percent Male		-0.038 (0.112) [-0.259, 0.182]		-0.035 (0.156) [-0.341, 0.271]
Pronouns × Percent Male ²		0.020 (0.111) [-0.197, 0.238]		0.029 (0.152) [-0.268, 0.325]
Observations	7970	7970	7970	7970
Resume Controls	✓	✓	✓	✓
Job Controls	✓	✓	✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns derived from the logistic regression described in equation (4). The dependent variable is an indicator variable which equals 1 if the applicant received an interview request. 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 A25: Estimates of Discrimination Against Applicants who Disclose Pronouns (Alternative Positive Employer Response: Any Positive)

	(A)	(B)	(C)	(D)
Nonbinary Pronouns	-0.053*** (0.008) [-0.069, -0.037]	-0.053*** (0.008) [-0.069, -0.037]	-0.054*** (0.008) [-0.069, -0.038]	-0.053*** (0.008) [-0.069, -0.037]
Binary Pronouns	-0.022* (0.012) [-0.045, 0.002]	-0.020* (0.012) [-0.043, 0.003]	-0.020* (0.012) [-0.043, 0.003]	-0.020* (0.012) [-0.043, 0.003]
Observations	7970	7970	7970	7970
Resume Controls		✓		✓
Job Controls			✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns derived from the logistic regression described in equation (1). The dependent variable is an indicator variable which equals 1 if the applicant received a response that could be interpreted as positive. 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 A26: Estimates of Gender Identity-Based Discrimination Against Nonbinary Applicants who Disclose Pronouns (Alternative Positive Employer Response: Any Positive)

	(A)	(B)	(C)	(D)
Nonbinary Pronouns	-0.031* (0.016) [-0.061, 0.000]	-0.032** (0.015) [-0.061, -0.002]	-0.034** (0.015) [-0.063, -0.004]	-0.032** (0.015) [-0.062, -0.002]
Observations	3985	3985	3985	3985
Resume Controls		✓		✓
Job Controls			✓	✓

Note: This table 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 derived from the logistic regression described in equation (2); only treated observations are included. The dependent variable is an indicator variable which equals 1 if the applicant received a response that could be interpreted as positive. 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 A27: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Geographic Politics (Alternative Positive Employer Response: Any Positive)

	Nonbinary Pronouns		Binary Pronouns	
	(D1)	(D2)	(D1)	(D2)
Pronouns	-0.036*** (0.011) [-0.058, -0.014]	0.189* (0.107) [-0.021, 0.399]	-0.012 (0.016) [-0.044, 0.020]	0.078 (0.185) [-0.285, 0.440]
Pronouns \times Republican	-0.035** (0.016) [-0.066, -0.003]		-0.015 (0.024) [-0.062, 0.032]	
Pronouns \times Vote Share		-0.927** (0.470) [-1.847, -0.006]		-0.363 (0.714) [-1.762, 1.036]
Pronouns \times Vote Share ²		0.810* (0.455) [-0.081, 1.701]		0.320 (0.690) [-1.032, 1.671]
Observations	7970	7970	7970	7970
Resume Controls	✓	✓	✓	✓
Job Controls	✓	✓	✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns 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 response that could be interpreted as positive. 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 A28: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions (Alternative Positive Employer Response: Any Positive)

	Nonbinary Pronouns		Binary Pronouns	
	(D1)	(D2)	(D1)	(D2)
Pronouns	-0.021 (0.024) [-0.068, 0.026]	0.150 (0.138) [-0.120, 0.420]	-0.036 (0.033) [-0.100, 0.029]	0.024 (0.217) [-0.401, 0.450]
Pronouns \times Implied Male	0.007 (0.017) [-0.026, 0.039]	0.007 (0.017) [-0.026, 0.039]	0.000 (0.024) [-0.048, 0.047]	0.000 (0.024) [-0.048, 0.047]
Pronouns \times Republican	-0.035** (0.016) [-0.067, -0.004]		-0.016 (0.024) [-0.063, 0.030]	
Pronouns \times Vote Share		-0.923** (0.470) [-1.845, -0.001]		-0.357 (0.717) [-1.764, 1.049]
Pronouns \times Vote Share ²		0.806* (0.455) [-0.086, 1.699]		0.312 (0.693) [-1.046, 1.670]
Pronouns \times High Customer-Facing	-0.026 (0.023) [-0.071, 0.019]		0.015 (0.036) [-0.055, 0.085]	
Pronouns \times Low Customer-Facing	-0.036* (0.019) [-0.074, 0.002]		0.001 (0.029) [-0.056, 0.058]	
Pronouns \times O*NET Score		0.001 (0.003) [-0.004, 0.007]		0.002 (0.003) [-0.005, 0.009]
Pronouns \times O*NET Score ²		0.000 (0.000) [0.000, 0.000]		0.000 (0.000) [0.000, 0.000]
Pronouns \times Male-Dominated	-0.006 (0.023) [-0.052, 0.039]		0.036 (0.035) [-0.032, 0.104]	
Pronouns \times Female-Dominated	0.020 (0.021) [-0.022, 0.062]		0.026 (0.032) [-0.037, 0.089]	
Pronouns \times Percent Male		-0.022 (0.124) [-0.265, 0.221]		-0.071 (0.178) [-0.420, 0.278]
Pronouns \times Percent Male ²		0.008 (0.121) [-0.229, 0.244]		0.069 (0.172) [-0.268, 0.407]
Observations	7970	7970	7970	7970
Resume Controls	✓	✓	✓	✓
Job Controls	✓	✓	✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns derived from the logistic regression described in equation (4). The dependent variable is an indicator variable which equals 1 if the applicant received a response that could be interpreted as positive. 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 A29: Estimates of Pronoun-Based Discrimination by Relevant Experience

	Nonbinary Pronouns		Binary Pronouns	
	(D1)	(D2)	(D1)	(D2)
Pronouns	-0.054*** (0.016) [-0.086, -0.022]	-0.060*** (0.018) [-0.094, -0.025]	-0.030 (0.024) [-0.077, 0.017]	-0.029 (0.026) [-0.079, 0.022]
Pronouns \times Years Relevant	0.007 (0.010) [-0.013, 0.027]	0.028 (0.029) [-0.028, 0.084]	0.019 (0.015) [-0.012, 0.049]	0.014 (0.042) [-0.068, 0.095]
Pronouns \times Years Relevant ²		-0.007 (0.009) [-0.025, 0.010]		0.002 (0.013) [-0.024, 0.028]
Observations	7970	7970	7970	7970
Resume Controls	✓	✓	✓	✓
Job Controls	✓	✓	✓	✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns derived from the logistic regression described in equation (5). The dependent variable is an indicator variable which equals 1 if the applicant received an interview request. 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. Note that if an applicant has prior work experience in the same occupation, they are considered to have “relevant” work experience. For example, when applying for a janitor role, an applicant has relevant experience if they have janitorial experience.

Table A30: Estimates of Discrimination Against Applicants with Sex- and Pronoun-Based Minoritized Identities

	(D1)	(D2)
Implied Male	-0.047** (0.021) [-0.088, -0.006]	-0.046** (0.022) [-0.089, -0.004]
Implied Male \times Female Dominated	-0.003 (0.031) [-0.063, 0.057]	-0.014 (0.031) [-0.076, 0.048]
Implied Female \times Male Dominated	-0.109*** (0.024) [-0.157, -0.062]	-0.113*** (0.025) [-0.161, -0.064]
Nonbinary Pronouns	-0.054*** (0.008) [-0.071, -0.038]	-0.058*** (0.013) [-0.084, -0.031]
Binary Pronouns	-0.017 (0.011) [-0.040, 0.005]	-0.022 (0.020) [-0.061, 0.016]
Observations	7970	7970
Resume Controls	✓	✓
Job 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 (6). 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.

Table A31: Estimates of Discrimination Against Applicants who Disclose Pronouns: Including Select Control Variables

	(B)	(D)
Nonbinary Pronouns	-0.054*** (0.008) [-0.071, -0.038]	-0.054*** (0.008) [-0.071, -0.038]
Binary Pronouns	-0.017 (0.012) [-0.039, 0.006]	-0.017 (0.011) [-0.039, 0.006]
GED	0.017 (0.025) [-0.033, 0.067]	0.019 (0.025) [-0.031, 0.068]
Associate's	0.037 (0.025) [-0.011, 0.085]	0.039 (0.024) [-0.009, 0.087]
Bachelor's	-0.017 (0.023) [-0.062, 0.028]	-0.016 (0.023) [-0.061, 0.029]
Years Relevant	0.056*** (0.017) [0.023, 0.089]	0.058*** (0.017) [0.025, 0.091]
Years Relevant ²	-0.010** (0.005) [-0.020, 0.000]	-0.011** (0.005) [-0.020, -0.001]
Current Relevant	0.046* (0.024) [-0.001, 0.093]	0.048** (0.024) [0.002, 0.095]
Observations	7970	7970
Resume Controls	✓	✓
Job Controls		✓

Note: This table reports average marginal effects associated with disclosing pronouns compared to not disclosing pronouns derived from the logistic regression described in equation (1). Estimates for select control variables are also shown. The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Years relevant equals years of “relevant” work experience an applicant has, where experience is considered “relevant” if it is in the occupation being applied for (e.g., janitorial experience is relevant when applying to a janitor job posting). Current relevant equals 1 if the applicant’s most recent work experience is “relevant.” 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.