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

Taryn Eames*

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Abstract

Nonbinary people have a gender identity that falls outside the male-female binary. To investigate hiring discrimination against nonbinary applicants, I submitted nearly 8,000 applications to postings in pairs. Treated resumes listed pronouns, and two treatment arms were considered: nonbinary "they/them" and sex-congruent "he/him" or "she/her." Results show disclosing "they/them" reduces employer response by 18% on average. Using the sex-congruent treatment arm as a disclosure-only benchmark, I decompose the "they/them" effect into a general disclosure penalty and an identity-specific component. I find around two-thirds of total "they/them" discrimination is rooted in nonbinary identity. Discrimination against applicants who disclose "they/them" pronouns is larger in Republican geographies and when job postings list narrow wage ranges.

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

*PhD Candidate, Department of Economics, University of Toronto, 150 St. George Street, Toronto, Ontario, Canada (email: taryn.eames@mail.utoronto.ca). 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, David Price, Patrick Button, and Andràs Tilcsik for helpful suggestions and feedback. I also thank Peter Cziraki for a Research Fellowship associated with this study. 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).

Nonbinary people, who often use gender-neutral pronouns such as "they/them," face unique challenges in the labor market. As pronoun sharing becomes increasingly common in social interactions and the workplace, there are more opportunities for nonbinary people to disclose their pronouns, reducing the risk of misgendering—a highly stressful experience (Corby et al. 2025).[1] This practice has recently extended to the labor market: job seekers now have the option to include pronouns on resumes, and 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 presumably cisgender applicants who disclose binary "he/him" or "she/her" pronouns is also investigated. By comparing discrimination faced by nonbinary and presumably 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 and by the applicant's nonbinary gender identity.

The growing prevalence of nonbinary gender identities, especially among younger generations, motivates this research. 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. Further, nonbinary people experience relatively poor labor market outcomes. Research consistently shows that transgender people (some of whom identify as nonbinary)

[1] Being misgendered means being referred to with pronouns or gendered terms that do not match one's gender identity.

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 in the U.S. have lower incomes compared to transgender men and women. This is consistent with Carpenter et al. (2024a) who find that, in Canada, nonbinary females in particular face worse economic outcomes than cisgender and transgender people. In addition, nonbinary people report facing significant intolerance and discrimination (James et al. 2016; Coffman et al. 2024). This provides suggestive evidence for discrimination as a driver of worse economic outcomes for nonbinary people.

At the same time, the U.S. legislative and policy landscape has become increasingly and disproportionately focused on transgender people. In recent years, there has been a dramatic surge in anti-transgender legislation—including bills that restrict access to gender-affirming healthcare, ban gender identity education in schools, require teachers to "out" transgender students to their parents, bar transgender athletes from participating in sport in a way that aligns with gender identity, and limit access to public facilities such as bathrooms. In 2019, 32 such bills were introduced and considered at the state and federal levels across the U.S.; in 2021, 143 bills were considered (and 19 were passed into law); in 2024, 674 bills were considered (and 50 passed into law) (Trans Legislation Tracker 2025a,b). Some of these bills specifically relate to nonbinary people in the workplace. For example, in 2024 House Bill 599 was considered in the Florida Senate, and stated "an employee or a contractor may not provide to an employer his or her preferred personal title or pronouns if such preferred personal title or pronouns do not correspond to his or her sex" (Florida House of Representatives 2024). While this bill ultimately did not pass, it is indicative of the kinds of policy discussions increasingly happening across the U.S. As such, investigating discrimination against this group is warranted and timely.

Popularized in economics 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; Lippens et al. 2023 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 (Levy et al. 2017; Jansson and Fritzson 2022; Abbate et al. 2023; Fumarco et al. 2024). In general, these studies find evidence of discrimination against transgender applicants.[2] 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) that are either marginally significant or statistically insignificant depending on specification. Finally, Business.com conduct a 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 is the first large-scale correspondence experiment centered on hiring discrimination against applicants who disclose pronouns. Between May and October 2023, I submitted 7,970 paired applications to postings in 15 occupations across six U.S. cities. Unlike Kline et al. (2022), who exclusively sample 108 very large Fortune 500 companies, my design samples broadly across many employers and employer types. This matters: very large

[2] Maupin and and (2024) is an exception, finding that applicants who list pronouns in their email signature, both binary and nonbinary, experience positive discrimination when contacting admission counselors of higher education institutions and requesting application information.

companies often have different hiring practices than smaller companies. Indeed, Kline et al. (2022) find that companies with more centralized hiring practices exhibit less discrimination. It also matters for technology: Applicant-tracking systems (ATS) are nearly ubiquitous in Fortune 500 firms (99% use ATS) but less common among other firms (66% of large firms; 35% of small organizations; Myers 2023). A core functionality of these systems is to parse resumes and organize extracted data into a standardized format in a central database (Find-Ernest 2023). This may not matter for name-based identity signals, but it does matter for signals conveyed via pronoun disclosure on a resume PDF: pronouns do not appear to be extracted by ATS.[3] For these reasons, the external validity of Kline et al. (2022) may be limited to very large employers and not reflective of discrimination more generally. Moreover, because that study focuses on firm-specific racial contact gaps, there is little to no discussion of the potential for nonbinary discrimination, beyond briefly reporting findings. By contrast, this paper offers an in-depth discussion of nonbinary discrimination—the signals carried by pronoun disclosure, potential mechanisms, and correlates of variation in contact penalties.

A key contribution of this paper is the decomposition of discrimination against applicants who disclose "they/them" pronouns into two components: the penalty from pronoun disclosure itself (which cisgender applicants who disclose pronouns also face) and the penalty attributable to their nonbinary gender identity.[4] This is important because in recent years, disclosing one's pronouns has become divisive in and of itself. Sentiment is 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 may include assumed party affiliation but also broader attitudes toward transgender people and identities. This is especially pertinent since

[3] To investigate this, in March of 2024, 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.

[4] While Kline et al. (2022) include applicants who disclose gender-neutral and gender-typical pronouns, they do not unpack what signals such disclosures may convey to employers or where those signals overlap.

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 focuses on two primary research questions. First, on average, do applicants who disclose nonbinary "they/them" pronouns during the hiring process experience discrimination? Second, 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 presumably cisgender applicants who disclose binary pronouns. Secondary hypotheses, informed by existing research and described below, are also explored. These hypotheses consider heterogeneity in the magnitude of discrimination given applicant, geographic, occupation, and job posting characteristics. Due to limited power, secondary hypotheses focus on total discrimination against nonbinary applicants (both identity-specific and due to the act of pronoun disclosure).

First, by collecting data from six cities across three states, with one Democratic-leaning and one Republican-leaning city in each, I consider whether discrimination differs geographically along political lines. This is motivated by evidence that discrimination against LGBTQ 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 the 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); a recent survey experiment shows that, in a lab setting, Republican respondents are more likely to discriminate against nonbinary job applicants (Pickett et al. 2024).

Second, I consider whether discrimination varies with the wage information in job postings.[5] I consider two dimensions: the posted wage level and the posted wage-range width (for example, $13-$17 versus $14-$16 versus a single wage $15). Higher-paying firms may have greater opportunity to discriminate—because they attract larger applicant pools and can be more selective—but they may also have more formal HR processes and stronger institutional accountability that reduce discrimination. Likewise, wider posted ranges could signal openness to candidates with diverse experiences and qualifications (reducing discrimination), or they could enable employers to defer discrimination to the wage-setting stage rather than the offer stage. This would lower observed rejection-stage discrimination without reducing overall disparate treatment.

Following Becker (1957), I also consider whether employers may discriminate 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 with 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 also investigate whether discrimination is larger when nonbinary appli-

[5]This analysis is exploratory and was not pre-specified in the pre-analysis plan (Eames 2023). The vast majority of job postings include wage information: 93.6% of the sample.

cants have male-sounding names.[6] This is motivated by evidence that, within the LGBT community, people assigned male at birth tend to experience worse labor market outcomes. This is true when it comes to gay and lesbian wage gaps (Black et al. 2003; Antecol et al. 2008; Drydakis 2012; Nauze 2015; Waite et al. 2019; Drydakis 2021; Jepsen and Jepsen 2022), gay and lesbian hiring discrimination (Flage 2020), and post-transition earnings for transgender men and women (Schilt and Wiswall 2008; Geijtenbeek and Plug 2018; Carpenter et al. 2024b). Finally, I consider the possibility of statistical discrimination (Arrow 1971; Phelps 1972) by comparing discrimination against applicants with more versus less relevant experience. Under statistical discrimination, discrimination should decrease as employers gain more information about an applicant's relevant skills and experience.

I find that disclosing "they/them" pronouns lowers the probability of a positive employer response by 5.6 percentage points (18%) relative to no pronoun disclosure. Relative to presumably cisgender applicants who disclose pronouns, the reduction is 3.9 percentage points (12%), implying that 69% of the total penalty is driven by applicant's nonbinary gender identity.[7] For scale, total discrimination against nonbinary applicants who disclose pronouns is similar to reducing relevant work experience[8] on the resume: from one to zero years (4.8 percentage points) or two to zero years (7.2 percentage points). Using study data, I also estimate comparable penalties for females in male-dominated occupations (7.0 percentage points) and for males in female-dominated or mixed occupations (4.7 percentage points). I find that discrimination is larger in Republican geographies and for postings with wide wage ranges—roughly twice as large as in Democratic geographies and for postings with narrow ranges, respectively. For presumably cisgender applicants who disclose pronouns, results are inconclusive: it is unclear whether these applicants experience no discrimination or some

[6]To consider differences in discrimination magnitude by implied sex, I assume employers use applicant first names to infer sex. This is discussed in the Online Appendix, Section A1.2.

[7]This share may be conservative if "they/them" disclosure carries positive signals that disclosing binary pronouns does not—such as authenticity or courageousness (see Ewens et al. 2014).

[8]'I define "relevant" work experience as prior work in the same occupation. For example, for a janitor posting, janitorial experience counts as relevant.

negative discrimination.[9]

This paper is structured as follows. Section 1 details the audit study design: resume construction, pronoun disclosure, geographic and occupational selection, and data collection. Section 2 describes the empirical strategy. Section 3 presents summary statistics, regression estimates, and robustness checks. Section 4 discusses and concludes.

1 Audit Study Design

A detailed description of the resume construction process is provided in the Online Appendix, including the randomization process, how inputs were sourced, and examples.

1.1 Resume Construction

Using a matched design, I constructed a pair of resumes for each job posting by randomizing education, work experience, and listed skills. Resume pairs are of similar quality—with the same education level, name-implied sex, and years of relevant work experience—while remaining different enough to realistically represent two distinct applicants. In each pair, exactly one resume was randomly assigned pronouns and the other listed none. Because my focus is identifying discrimination against nonbinary applicants, treated resumes have a two-thirds probability of listing "they/them" rather than "he/him" or "she/her" pronouns (congruent with name-implied sex).

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

[9]Using study data, Eames (2025) considers the intersection of sex and nonbinary identity; sex-based discrimination patterns mirror those for presumably cisgender applicants.

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.

1.2 Pronoun Disclosure

Pronoun disclosure is the treatment evaluated in this study. In the first treatment arm, 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 differ from other nonbinary applicants who are less open about their gender identity. This is a common limitation in correspondence studies of LGBTQ discrimination, where identity is typically signaled by voluntary disclosure of involvement in an LGBTQ organization (Tilcsik 2011; Bardales 2013; Mishel 2016; Flage 2020). In some respects, pronoun disclosure is a methodological improvement: unlike sexual orientation—which can be concealed without affecting how one is addressed—avoiding misgendering (which can cause dysphoria and distress Kerr et al. 2022; Bhatt et al. 2022) requires workplace identity disclosure for nonbinary people who use gender neutral pronouns. That being said, it is worth considering to what extent nonbinary applicants who list "they/them" pronouns on their resume are the same as or different from those who do not.

In the second treatment arm, 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 "presumably cisgender" and disclosing pronouns. While there is no guarantee employers will interpret the disclosure of binary pronouns this way, it is a reasonable expectation. First, LGBTQ 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." This far exceeds the 0.6% of U.S. adults who identify as transgender men and women (Brown 2022), indicating that most of these individuals are cisgender and disclosing binary pronouns.

1.3 Geography Selection

Core Based Statistical Areas (CBSAs) chosen for resume distribution are described in Table 1. Geographies were selected to include pairs of CBSAs that met three criteria. First, to ensure legislative consistency, CBSAs are in states with explicit statutes prohibiting employment discrimination based on gender identity and sexual orientation.[10] Second, CBSAs have a population of at least 500 thousand to ensure sufficient job postings. Third, within each state, CBSA pairs differ politically, with one Democratic-leaning and one Republican-leaning (classified by 2020 presidential vote share). Table 1 shows that political leanings are stable over time in relative terms: from 2000 to 2020, in each state pair the Republican-leaning CBSA's Republican vote share exceeded its Democratic-leaning counterpart by at least 15 percentage points. In all, this design prioritizes consistency in macroeconomic environments

[10] *Bostock vs Clayton County, Georgia* (2020) held that discrimination based on sexual orientation or gender identity is prohibited under Title VII's ban on discrimination "because of sex." However, no federal statute explicitly names sexual orientation or gender identity as protected classes (Minkin and Brown nd).

as well as state policy and legislation, to focus on attitudinal differences between Democratic and Republican regions.

An implication of restricting the sample to states that explicitly prohibit employment discrimination based on sexual orientation and gender identity 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 reported should be interpreted as conservative—likely representing a lower bound.

1.4 Occupation Selection

Fictitious resumes were sent in response to postings in the occupations listed in Table 2. 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 is classified as male-dominated (over two-thirds of workers are male), female-dominated (less than one-third male), or mixed (in between). Customer interaction is classified as high, medium, or low; 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).[11] 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 generally 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

[11] Occupations with scores above 75 are deemed high customer-facing, between 50 and 75 medium, and below 50 low.

interaction. This requires applying across a range of occupations which is less feasible in higher-skill occupations where there are more barriers to application (for example, 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 (for example, 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 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.

1.5 Data Collection Process

Between May and October 2023, a team of Research Assistants (RAs) submitted 7,970 fictitious resumes in matched pairs to 3,985 job postings on a large online job board. Each week, every RA was assigned a fictitious applicant profile and applied to jobs on that applicant's behalf. RAs were given weekly target lists designed to balance application counts across occupation, sex, and geography. For each job posting, the matched resume was submitted between 12 and 36 hours after the first application.

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, located within 25 miles of the target city, and located in the correct state. RAs briefly read each job posting to confirm that the job was categorized appropriately, did not require more than one year of occupation-specific experience, was not a supervisory or managerial role, and did not demand qualifications not typically included in resumes. A tracking system was used to ensure we did not apply more than once to a job posting under the same company name in the same state. If a potential duplicate was identified, the posting was rendered ineligible, with two exceptions: when the first paired application occurred at least three weeks earlier, the position was in a different occupation, and the implied sexes of the two applicants differed; or when the applications were sent to distinct franchisees operating under the same company name. These exceptions account for well under 1% of observations. In addition, RAs checked company names against a list of hundreds of job agencies. Any posting from a job agency was rendered ineligible, as such firms typically respond positively to all applicants in order to place a wide range of workers (regardless of skill or experience), making them poor experimental targets.

Finally, some job postings required applicants to answer questions during the application process. When the requested information was available on the resume (for example, "what is your highest education level?" or "how many years of janitorial experience do you have?"), RAs provided an answer. When a question required subjective or other information unavailable in the resume (for example, "how would you describe your teamwork style?" or "why are you interested in this job?"), answers were left blank. In total, blank answers were left as part of 5.6% of applications.[12] Job postings that required applicants to manually enter detailed work histories—effectively having the applicant duplicate their resume—were rendered ineligible. This criterion was motivated both by feasibility (these applications are too time-consuming) and by experimental integrity, since such forms typically do not allow pronoun disclosure, eliminating the treatment signal. Similarly, postings that did not require a resume were also rendered ineligible, as employers are unlikely to open and review uploaded resume PDFs, preventing any pronoun signal from being communicated.

[12] Cases where leaving a field blank was an explicit option are not included in the 5.6%—for example, when applicants were asked whether they had been referred by a current employee (for example, "If yes, please provide their name; if not, leave blank"). While this information was generally recorded, it was not originally planned for analysis. Some cases may therefore have gone undocumented, though such instances are expected to be rare.

Employer responses (received via voicemail, text message, email, or direct message through the job board) were carefully tracked and categorized, with positive employer response as the outcome of interest. Following the study's pre-analysis plan, "employer response [is] viewed as 'positive' if they contact the applicant and either offer an interview or request the applicant contact them" (Eames 2023). This excludes responses that 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.[13] Robustness checks using both more and less restrictive definitions of positive response are described in Section 3.4; under the less restrictive definition, such ambiguous messages are classified as positive.

Application pronouns were blinded during response tracking and categorization. Evaluators were provided only the information contained in the employer's response (company name, applicant name, and location) and used this to match responses to the corresponding applications. Even at this stage, responses were mapped only to application IDs, with no information on pronouns accessible to the evaluator.

2 Empirical Strategy

A pre-analysis plan (PAP) for this study is registered in the American Economic Association Randomized Controlled Trial Registry (Trial #11183; Eames 2023). Following Duflo et al. (2020), a populated version of the PAP is available in the registry documents, where all pre-specified analyses are implemented as planned. The empirical strategy employed here closely follows that design, and despite minor methodological refinements, results remain nearly identical. One additional analysis, not pre-specified in the PAP, examines whether the magnitude of discrimination differs across job postings with high versus low posted wages

[13] For example: "Hey Hannah! This is [name] the recruiter for [company name]. I just received your resume. Thank you for sending it over! We're hiring and I'd love to help you with the next steps. You are interested in working at [company name], right?"

and with wide versus narrow wage ranges.[14]

To estimate average discrimination against applicants who disclose pronouns, I estimate the following logistic regression model, from which average marginal effects (AMEs) are derived and interpreted as the key measure of discrimination:

$$\log\left(\frac{p_{iocj}}{1-p_{iocj}}\right) = \gamma P_i + \lambda NB_i + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj} \tag{1}$$

where $p_{iocj} = \Pr(y_{iocj} = 1)$, y_{iocj} equals 1 if applicant i received a positive response from job posting j in occupation o and CBSA c, P_i is an indicator variable which equals 1 if the resume lists pronouns (regardless of which ones), NB_i is an indicator variable which equals 1 if the resume specifically lists nonbinary "they/them" pronouns, X_i and Z_j are vectors of applicant and job controls that may affect baseline response rates, η_o and δ_c are occupation and CBSA fixed effects, and ε_{ij} is the idiosyncratic error term. Standard errors are clustered at the job posting level.

Resume characteristics in vector X_i include timing variables (whether the resume was sent first and the lag between the two applications), indicators for education level and listed skills, and work experience variables capturing the years and timing of relevant and common work experiences. Job posting characteristics in vector Z_j include estimated application volume and standardized measures of posted wages (within occupation and CBSA). Detailed descriptions of all control variables are provided in Appendix Tables A4 and A5.

The AMEs associated with γ and λ capture distinct components of discrimination. The AME for γ represents discrimination against applicants who disclose any pronouns, including presumably cisgender individuals listing "he/him" or "she/her." In contrast, the AME for λ captures additional discrimination faced by applicants who disclose "they/them" pronouns specifically. To estimate the share of total discrimination against "they/them" applicants

[14]The realized sample size exceeds the "target" sample size outlined in the PAP. Data collection was pre-specified to occur from May to October 2025, with the option to continue if the target sample size was not reached. In practice, the target was achieved and surpassed within this period, resulting in a larger final sample.

attributable to their nonbinary gender identity, define the decomposition parameter θ:

$$\theta = \frac{\lambda}{\gamma + \lambda} \tag{2}$$

The remaining share $(1-\theta)$ is attributable to the act of pronoun disclosure itself, which also affects presumably cisgender applicants.

Importantly, while I assume above that the effects of pronoun disclosure and nonbinary identity are additive, this may not be strictly true. If the cost of pronoun disclosure differs by identity, then the act of disclosure may convey a different underlying signal to employers (Ewens et al. 2014). I expect that, if this is the case, (2) will overstate the share of discrimination driven by the act of pronoun disclosure (and aside from gender identity). For example, if nonbinary applicants anticipate discrimination and are aware that they face higher costs when disclosing pronouns, disclosure may signal positive traits—like authenticity, courage, or confidence in their own quality and ability to find a job even in the face of anticipated discrimination. Similarly, employers who are transphobic may penalize any pronoun disclosure—including "he/him" or "she/her"—precisely because they interpret it as support for transgender inclusion. If so, the penalty is still identity-based rather than a general aversion to listing pronouns or a generic political signal—again, (2) will understate the share of discrimination driven by identity.

To investigate secondary hypotheses regarding heterogeneity in discrimination, I estimate:

$$\log\left(\frac{p_{iocj}}{1-p_{iocj}}\right) = \gamma_1 P_i + [P_i \cdot I']\gamma_2 + \lambda_1 NB_i + [NB_i \cdot I']\lambda_2 + X_i'\beta_1 + Z_j'\beta_2 + I'\beta_3 + \eta_o + \delta_c + \varepsilon_{iocj} \tag{3}$$

where I is a vector of indicator moderators specific to each secondary hypothesis. AMEs from γ_1 and λ_1 represent average discrimination for the baseline group (when $I = 0$), while AMEs from γ_2 and λ_2 represent the difference in discrimination between the baseline and non-baseline group (when $I = 1$). To test whether discrimination magnitude varies by geographic politics, I is R_c which equals 1 if the CBSA is categorized as Republican. To consider posting wage, I is HW_j which equals 1 if the job posting has a high wage; separately, to consider posting wage range, I is HWR_j which equals 1 if the job posting has a wide wage range. To consider relevant experience (and thus statistical discrimination), I is RE_i which equals 1 if the applicant has at least one year of relevant experience. To consider occupation customer-facing interaction, I includes HCF_o and LCF_o which equal 1 if the occupation is high customer-facing and low customer-facing respectively. Finally, to consider occupation worker sex composition, I includes MD_o and FD_o which equal 1 if the occupation is male- and female-dominated respectively. Detailed descriptions of all interaction variables are available in the Online Appendix.

3 Results

3.1 Summary Statistics

Figure 1 shows positive employer response rates by pronoun disclosure group and pairwise Chi-squared tests. The baseline response rate for applicants who do not disclose pronouns is 31.3%. While this is higher than rates reported in earlier correspondence studies, it aligns with recent work focused on lower-skilled occupations (for example, Neumark et al. 2019a). Applicants who disclose binary "he/him" or "she/her" pronouns receive a slightly lower response rate of 29.4%, though this difference is not statistically significant relative to the baseline. In contrast, applicants who disclose nonbinary "they/them" pronouns face a substantially lower response rate of 25.8%, a difference that is statistically significant both relative to the baseline and to the binary pronoun group.

Table 3 reports the same information by geography (state and CBSA), and Table 4 by occupation. Across these groups, the raw reduction in response rate associated with pronoun disclosure is generally larger—and statistical significance stronger—when "they/them" pronouns are disclosed than when presumably cisgender applicants disclose "he/him" or "she/her." Differences in the magnitude of this reduction appear negligible across states but substantial across CBSAs, broadly tracking local political leanings (with the exception of Utah). Baseline positive employer response rates vary considerably across occupations, ranging from 16.1% to 47.5% among applicants who do not disclose pronouns. Unsurprisingly, within a single occupation, the statistical significance of response rate gaps between treated and control applicants is limited given the small sample sizes.

3.2 Primary Hypotheses: Average Discrimination

Table 5 reports AMEs from equation (1), including estimates of discrimination and selected control variables. Results are shown for specifications with and without covariates and fixed effects; estimates are consistent across columns. The preferred specification (column 4) includes resume and job-posting controls as well as occupation and CBSA fixed effects. In this model, the average effect of disclosing pronouns generally is not statistically significant.[15] That said, the 95% confidence interval [-0.040, +0.006] rules out economically meaningful positive discrimination—these applicants either fact no discrimination or some negative discrimination. Relative to applicants who disclose binary pronouns, those disclosing nonbinary "they/them" experience a 3.9 percentage-point (13%) lower probability of a positive employer response. In total, relative to no disclosure, "they/them" disclosure lowers the response rate by 5.6 percentage points (18%). From equation (2), I estimate that 69% of the discrimination faced by applicants who disclose "they/them" pronouns is rooted in their nonbinary gender identity rather than the political and other signals associated with the act of pronoun disclosure.

To contextualize these discrimination estimates, I compare them with coefficients on resume controls that shift baseline response rates. Relevant work experience materially increases employer response: moving from zero to one year of relevant experience raises the probability of a positive employer response by 4.8 percentage points, and from zero to

[15] Appendix robustness checks consider alternative specifications; this estimate is statistically significant in of the eight alternatives considered, (see Table A16).

two years by 7.4 percentage points.[16] Listing that experience as the current job, rather than a past job, further increases the likelihood of a response. Against these benchmarks, the total penalty associated with disclosing "they/them" pronouns (5.6 percentage points or 18%) is comparable to losing one to two years of relevant experience or to presenting relevant experience as prior rather than current employment. As an additional reference point, I estimate sex-based penalties (where sex signaled by applicant name) using the same field experiment data (see Appendix Section A2.7). I find that female applicants face a 7.0 percentage point penalty (20%) in male-dominated occupations, and male applicants receive a 4.7 percentage point penalty (13%) in female-dominated and mixed occupations. The total penalty associated with disclosing nonbinary penalty is of comparable in magnitude, but—unlike the sex penalties—applies across all occupation categories.

3.3 Secondary Hypotheses: Heterogeneous Discrimination

Figure 2 reports AMEs from equation (3) that trace how the total effect of disclosing "they/them" pronouns varies across subgroups. Reported estimates reflect the combined effect of pronoun disclosure in general and the additional penalty associated with nonbinary gender identity; full regression tables with separate components are provided in Appendix Tables A12 and A13. In several subgroup comparisons—by applicant relevant experience, job posting wage, occupation worker sex composition, and occupation customer-facing interaction—point estimates differ minimally across groups. However, these results are statistically inconclusive: there is no evidence of heterogeneous discrimination, but the estimates lack sufficient precision to rule out meaningful differences. This applies to the statistical discrimination hypothesis: if this were present, discrimination should decline as relevant experience increases (employers can rely less on statistical priors once concrete evidence of occupation-specific competence is available). The results do not exhibit this pattern, but do not conclusively rule it out either.

[16] Work experience is "relevant" when it is in the target occupation. For example, janitorial experience is relevant when applying for a janitor posting.

However, two subgroups show statistically significant heterogeneity. The first is by CBSA political partisanship.[17] In Democratic CBSAs, the estimated discrimination against applicants disclosing "they/them" pronouns is 3.6 percentage points (11%). By comparison, discrimination is 4.0 percentage points higher—approximately double—in Republican CBSAs, at 7.6 percentage points (25%). This may be driven by attitudinal differences: by focusing within-state, I control for state-level macroeconomic factors, policy, and legislation. Further, two of the three geographic pairs are neighboring (within 75 miles), increasing their environmental similarities. However, it may be something else: geographic politics are likely correlated with many latent factors that may lead to differences in discrimination. For example, Appendix Table A10 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; and percent white and number of religious congregations per 100K are smaller. These trends hold for the geographies in this study's research sample.

Second, discrimination varies by the wage range width listed in the job posting.[18] When the wage range is narrow—meaning it falls below the average range for job postings within the same occupation and CBSA—total discrimination against applicants who disclose "they/them" pronouns is substantial, at 7.1 percentage points (21%).[19] In contrast, when the wage range is wide, estimated discrimination falls by 4.4 percentage points, to 2.7 percentage points (10%), and is not statistically different from zero. Several mechanisms could explain this pattern. Employers posting wide ranges may be targeting a broader applicant pool and thus be more open to diverse candidates. Alternatively, these employers may be deferring discriminatory behavior to the wage-setting stage—rather than rejecting nonbinary applicants outright, they may instead offer them lower pay. If so, this may not reflect a "true" reduc-

[17] In the Appendix, I also categorize political partisanship at the county level and conduct other alternative specification; results are consistent with those shown here (see Appendix Table A17).

[18] The vast majority of job postings included wage information: 93.6% of the sample.

[19] In the Appendix, I use an alternative binary classification based on whether the posting includes a single wage (narrow) versus some range (wide) and conduct other alternative specifications; results are consistent with those shown here (see Appendix Table A18).

tion in disparate treatment; only a reduction in observed discrimination at the interview offer stage. Finally, it may reflect systematic differences employer type: those who post wide wage ranges could differ from those who post narrow ones in unobserved ways (for example, in their resources or HR practices) that are correlated with discrimination. Hence, these interpretations are suggestive rather than causal.

3.4 Robustness Checks and Other Analyses

I conduct an extensive set of robustness checks and ancillary analyses; full details and results are reported in the Online Appendix.

First, considering average treatment effects associated with the primary research questions, I address the Heckman-Siegelman critique using the approach outlined in Neumark (2012).[20] Although statistical power is limited to cleanly disentangle the general effect of pronoun disclosure from the incremental penalty for disclosing "they/them," the total discrimination estimate for nonbinary applicants who disclose pronouns remains robust, statistically significant, and similar in magnitude to the main estimates. I then re-estimate the preferred specification from Table 5 (column 4) under multiple alternative specifications: (i) replacing the logistic model with a linear probability model (OLS), estimated both with the baseline fixed effects and, alternatively, with job-posting fixed effects (that is, a fixed effect for each application pair); (ii) applying observation weights following Solon et al. (2015); Neumark et al. (2019b) to align the experimental sample with the occupation distribution in the study geographies; (iii) redefining "positive employer response" using both a less strict criterion (classifying any plausibly positive response as positive—for example, requests to complete an application on the firm's website) and a stricter criterion (only explicit interview requests); and (iv) excluding the 5.6% of cases in which employers asked a question that RAs did not answer (see Appendix Section 1.5). Across these exercises, the average effects are substantively unchanged.

[20] Heckman and Siegelman (1993) and Heckman (1998) show that correspondence studies may be biased if the variance of unobserved productivity differs between treatment and control groups.

I apply the same suite of modifications to the heterogeneous treatment-effect analyses. In addition, following Hull et al. (1992); Yzerbyt et al. (2004), I estimate a saturated version of equation (3) that fully interacts each subgroup indicator with all control variables. Heterogeneity results remain consistent with those reported in the main text.

Finally, because experimental detection can attenuate estimated discrimination—either via social-desirability inflation toward treated applicants or by employers ceasing contact with applicants who appear "off" (Balfe et al. 2023)—I test for order-based detection by comparing responses for applicants sent first versus second. I find no evidence that this experiment was detected among employers (see Appendix Section A2.6).

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 treatments arms were evaluated: disclosing 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 5.6 percentage points (18%). Comparing applicants who disclose "they/them" pronouns to presumably cisgender applicants who disclose "he/him" or "she/her" pronouns, the former experience an additional 3.9 percentage point reduction in positive employer response (13%). Hence, for applicants disclosing "they/them" pronouns, 69% of discrimination is estimated to be rooted in their nonbinary gender identity rather than the act of pronoun disclosure more generally. These estimates likely reflect a lower bound for the U.S., 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 presumably cisgender applicants who disclose pronouns is inconclusive: I am unable to determine if these applicants face no discrimination or some negative discrimination: the 95% confidence interval spans -4.0 to +0.6 percentage points.

These findings are notably different from Kline et al. (2022), who find a smaller and marginally significant "they/them" penalty of 1.7 percentage points. Not only does their point estimate lies outside the 95% confidence interval found here (-7.1 to -4.1 percentage points), their lower bound (-3.4 percentage points) does too. One interpretation is that hiring practices at very large firms (in their sample) differ from smaller companies (included in this sample), resulting in different levels of initial-stage discrimination. Indeed, Kline et al. (2022) find less discrimination among firms with more centralized hiring practices. Very large companies also use different technology in hiring—like Application Tracking Systems—which may blind pronoun disclosure by default, reducing observed discrimination. Shifts in sentiment towards transgender and nonbinary people may also matter: for Kline et al. (2022), data were collected from late 2019 to early 2021 (with a mid-2020 pause), whereas this study uses data collected in mid-2023. Between these years, anti-transgender legislation increased sharply (32 in 2019, 143 in 2021, 174 in 2022, 604 in 2023; Trans Legislation Tracker 2025a,b). Such policy discussion may reflect changing attitudes or influence public sentiment directly. Further, from 2022 to 2025, Pew Research Center (2025) find that public support for protecting transgender people from discrimination declined between 2022 and 2025. The similarity of estimates for binary pronoun disclosure across the two studies further supports the interpretation that changing attitudes—rather than design differences—may explain part of the observed difference.

Considering heterogeneity in discrimination magnitude, I find that discrimination against applicants who disclose "they/them" pronouns is approximately double in Republican than in Democratic geographies. 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. In addition, I find that discrimination is approximately double in job postings with narrow versus wide wage ranges. One interpretation is that wider ranges reflect greater flexibility, allowing employers to defer discriminatory behavior to wage setting rather than the hiring margin. A second is that wide-range posters are more open to diverse applicants—consistent with recruiting from a broader range of backgrounds. A third is compositional: wage-range width may proxy for unobserved employer characteristics that are correlated with lower measured discrimination. For all other secondary hypotheses, discrimination results are inconclusive—generally unsurprising given limited power.

While the evidence for statistical discrimination is inconclusive, productivity-based statistical discrimination appears unlikely. In 2021, 74% of Americans reported not personally knowing anyone who uses gender-neutral pronouns (Minkin and Brown 2021), which makes it implausible that most employers could form accurate productivity-related priors about this group.[21]

By contrast, taste-based discrimination is more plausible given the U.S. policy environment and the larger penalties observed in Republican areas. For example, 16% of Americans openly opposed protecting transgender people from discrimination in 2025—up from 10% in 2022 (Pew Research Center 2025). Even employers supportive of inclusion may unintentionally discriminate when they have limited exposure to gender-nonconforming individuals: because most people lack practice using gender-neutral pronouns, perceived social costs of the learning curve—discomfort about making mistakes or fear of offending their new hire—may deter hiring nonbinary applicants.

[21] That said, inaccurate priors may exist—for example, based on media-driven stereotypes about nonbinary people.

Taken together, results show that "they/them" pronoun disclosure leads to hiring discrimination that is primarily rooted in an applicant's gender identity. This motivates further research focused on the labor market and hiring experiences of nonbinary people—especially given the growing number of young people identifying as nonbinary—and gender nonconforming more broadly. Future research could examine the impact of pronoun disclosure in higher-skill occupations, more deeply explore whether company size influences nonbinary discrimination, and investigate whether employers who post wide wage ranges substitute discrimination at the hiring stage with discriminatory wage setting. Understanding the specific barriers nonbinary workers face when it comes to use of gender-neutral pronouns may be important—especially currently, when most people have limited experience using gender-neutral pronouns to refer to an individual.

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Tables and Figures

Table 1: Geographies

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

Note: Core Based Statistical Area (CBSA) population count is listed in thousands and sourced from U.S. Census Bureau (2023a). 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 2: Occupations

	Worker Composition		Customer Interaction	
Occupation	% 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	Mixed	93	High
Server	36	Mixed	75	High
Cook	59	Mixed	52	Medium
Baker	44	Mixed	37	Low
Assembler / Fabricator	62	Mixed	17	Low
Receptionist	9	Female-Dominated	87	High
Cashier	28	Female-Dominated	86	High
Housekeeper	15	Female-Dominated	58	Medium
Certified Nursing Assistant	11	Female-Dominated	47	Low
Administrative Assistant	6	Female-Dominated	47	Low

Note: worker count and composition data is from the 2019 American Community Survey (U.S. Census Bureau 2022b). 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.

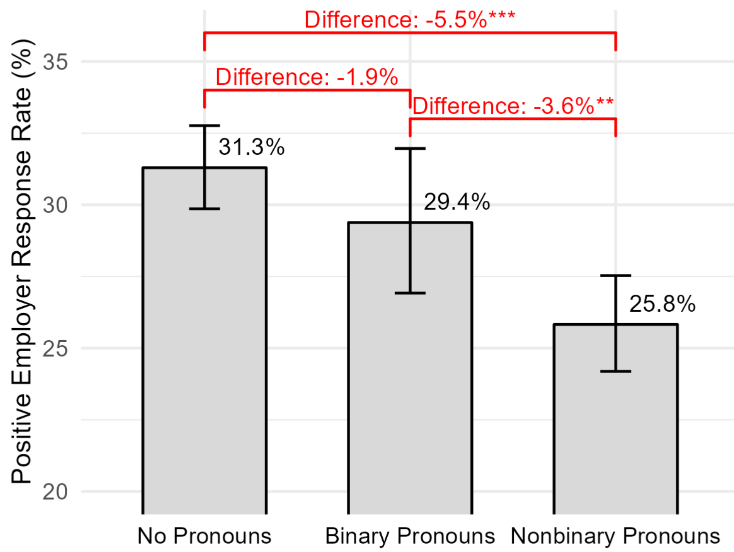


Figure 1: Positive Employer Response by Pronoun Disclosure

Note: Bars show positive employer response rates by pronoun condition. Vertical lines represent 95% confidence intervals for the true proportion. Red annotations display pairwise differences in response rates between groups. Stars indicate statistical significance, based on Chi-squared tests for equality of proportions: *** 1% level, ** 5% level, * 10% level.

Table 3: Chi-Squared Tests: Differences in Positive Employer Response by Geography

	Positive Employer Response						Sample Size		
Group	NP	NB	NB - NP	B	B - NP	NB - B	NP	NB	B
Panel A: Overall Results									
All Observations	0.313	0.258	-0.055 ***	0.294	-0.019	-0.036 **	3985	2695	1290
			(0.011)		(0.015)	(0.015)			
Panel B: Results by State									
Washington	0.307	0.251	-0.056 ***	0.286	-0.021	-0.035	1323	910	413
			(0.019)		(0.026)	(0.026)			
Colorado	0.316	0.259	-0.058 ***	0.296	-0.021	-0.037	1325	882	443
			(0.020)		(0.025)	(0.026)			
Utah	0.316	0.266	-0.050 **	0.30	-0.016	-0.034	1337	903	434
			(0.019)		(0.025)	(0.026)			
Panel B: Results by CBSA									
Seattle, WA	0.340	0.302	-0.038	0.332	-0.009	-0.029	664	453	211
			(0.028)		(0.037)	(0.039)			
Spokane, WA	0.273	0.199	-0.074 ***	0.238	-0.036	-0.038	659	457	202
			(0.025)		(0.035)	(0.035)			
Denver, CO	0.318	0.294	-0.024	0.304	-0.015	-0.009	666	442	224
			(0.028)		(0.036)	(0.038)			
Colorado Springs, CO	0.314	0.223	-0.091 ***	0.288	-0.026	-0.065 *	659	440	219
			(0.027)		(0.036)	(0.036)			
Salt Lake City, UT	0.305	0.253	-0.052 *	0.30	-0.005	-0.046	669	442	227
			(0.027)		(0.035)	(0.037)			
Provo, UT	0.326	0.278	-0.049 *	0.30	-0.027	-0.022	668	461	207
			(0.028)		(0.037)	(0.038)			

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. Column "NB - B" reports the difference in response rates between applicants who disclose nonbinary pronouns and those who disclose binary 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 4: Differences in Positive Employer Response by Occupation

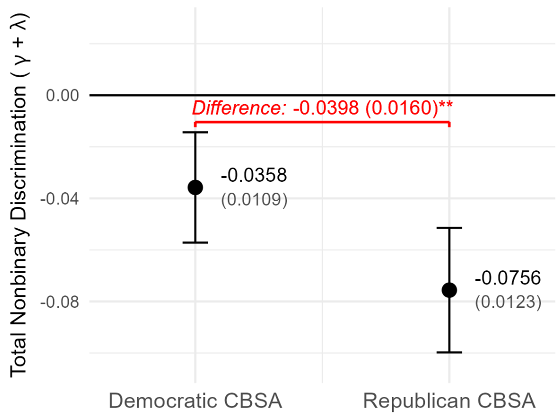
	Positive Employer Response						Sample Size		
Occupation	NP	NB	NB - NP	B	B - NP	NB - B	NP	NB	B
Panel A: Overall Results									
All Observations	0.313	0.258	-0.055 ***	0.294	-0.019	-0.036 **	3985	2695	1290
			(0.011)		(0.015)	(0.015)			
Panel B: Results by Occupation									
Administrative Assistant	0.161	0.116	-0.045	0.197	0.037	-0.082	218	147	71
			(0.036)		(0.053)	(0.054)			
Construction Worker	0.181	0.163	-0.018	0.189	0.008	-0.026	215	141	74
			(0.041)		(0.053)	(0.055)			
Receptionist	0.221	0.199	-0.022	0.204	-0.017	-0.005	299	201	98
			(0.037)		(0.047)	(0.050)			
Server	0.265	0.197	-0.068	0.250	-0.015	-0.053	200	132	68
			(0.047)		(0.061)	(0.063)			
Janitor	0.286	0.228	-0.057	0.345	0.060	-0.117 *	217	162	55
			(0.045)		(0.071)	(0.072)			
Assembler	0.295	0.248	-0.048	0.246	-0.049	0.002	166	105	61
			(0.055)		(0.066)	(0.069)			
Landscaper	0.310	0.234	-0.075	0.294	-0.016	-0.060	213	145	68
			(0.047)		(0.064)	(0.066)			
Truck Driver	0.313	0.262	-0.051	0.279	-0.034	-0.017	396	267	129
			(0.036)		(0.046)	(0.048)			
Warehouse Worker	0.316	0.253	-0.063	0.288	-0.028	-0.035	335	217	118
			(0.039)		(0.049)	(0.051)			
Housekeeper	0.319	0.298	-0.021	0.295	-0.024	0.003	229	151	78
			(0.048)		(0.060)	(0.064)			
Cook	0.324	0.291	-0.033	0.277	-0.046	0.013	346	227	119
			(0.039)		(0.048)	(0.051)			
Retail Sales	0.348	0.263	-0.085 ***	0.319	-0.029	-0.056	500	334	166
			(0.032)		(0.042)	(0.043)			
Cashier	0.362	0.309	-0.052	0.395	0.033	-0.085	177	139	38
			(0.053)		(0.087)	(0.088)			
Baker	0.462	0.348	-0.114	0.519	0.056	-0.170	93	66	27
			(0.078)		(0.109)	(0.113)			
Certified Nursing Assistant	0.475	0.395	-0.080 **	0.433	-0.042	-0.039	381	261	120
			(0.040)		(0.052)	(0.054)			

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. Column "NB - B" reports the difference in response rates between applicants who disclose nonbinary pronouns and those who disclose binary 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.

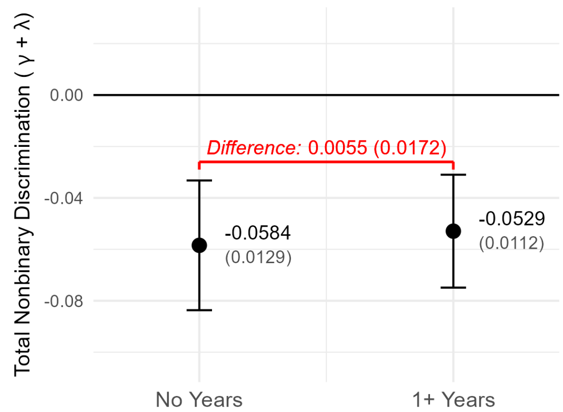
Table 5: Average Discrimination Estimates

	(1)	(2)	(3)	(4)
Panel A: Discrimination Estimates (Average Treatment Effects)				
Pronoun Disclosure (γ)	-0.019 (0.012) [-0.042, 0.005]	-0.019 (0.012) [-0.042, 0.004]	-0.017 (0.012) [-0.040, 0.006]	-0.017 (0.012) [-0.040, 0.006]
Nonbinary Gender Identity (λ)	-0.036** (0.015) [-0.066, -0.007]	-0.036** (0.015) [-0.065, -0.006]	-0.039*** (0.015) [-0.068, -0.009]	-0.039*** (0.015) [-0.068, -0.009]
Total "they/them" Disclosure ($\gamma + \lambda$)	-0.055*** (0.008) [-0.071, -0.039]	-0.055*** (0.008) [-0.070, -0.039]	-0.056*** (0.008) [-0.071, -0.041]	-0.056*** (0.008) [-0.071, 7.000]
Panel B: Select Control Variables				
Years of Relevant Experience		0.058*** (0.016) [0.027, 0.089]		0.060*** (0.017) [0.027, 0.093]
Years of Relevant Experience^2		-0.011** (0.005) [-0.021, -0.002]		-0.012** (0.005) [-0.021, -0.002]
Most Recent Experience is Relevant		0.049** (0.023) [0.004, 0.094]		0.050** (0.023) [0.005, 0.095]
Panel C: Specification Information				
Resume Controls		✓		✓
Job Posting Controls		✓		✓
Occupation Fixed Effects			✓	✓
CBSA Fixed Effects			✓	✓
Observations	7,970	7,970	7,970	7,970

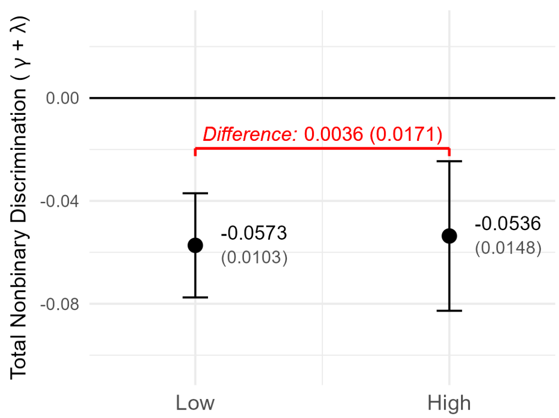
Notes: This table reports average marginal effects from the logistic model in equation (1). Pronoun disclosure (γ) is the average effect of listing any pronouns relative to listing none; this applies to presumably cisgender applicants as well. Nonbinary gender identity (λ) is the incremental effect of disclosing "they/them" versus binary pronouns. The dependent variable equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.



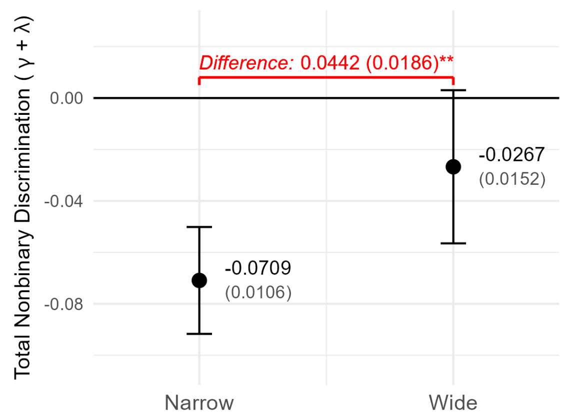
(a) Results by CBSA Politics



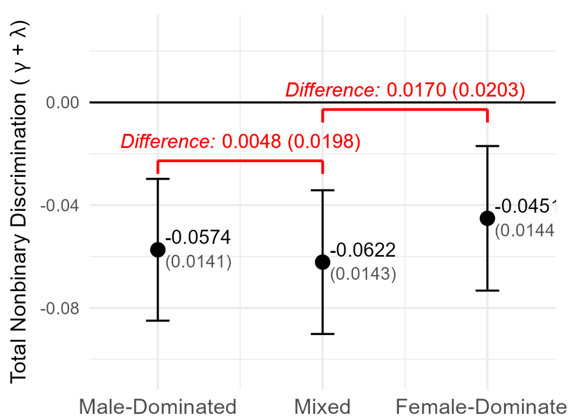
(b) Results by Relevant Experience



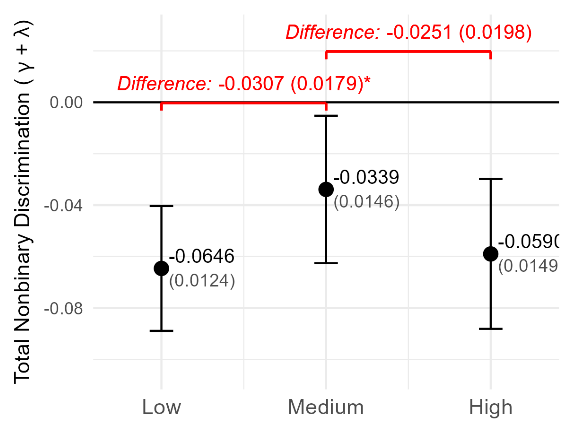
(c) Results by Job Posting Wage



(d) Results by Job Posting Wage Range



(e) Results by Worker Sex Composition



(f) Results by Customer-Facing Interaction

Figure 2: Heterogeneous Discrimination Estimates by Subgroup

Notes: Each dot is the estimated total penalty for disclosing "they/them" pronouns—the combined AMEs for (i) the act of pronoun disclosure and (ii) the incremental "they/them" penalty—from equation (3). Point estimates are reported to the right of the dots; vertical lines denote 95% confidence intervals. Red annotations report pairwise differences in discrimination between the displayed groups, also estimated from equation (3); standard errors (clustered at the job posting level) are in parentheses. Stars indicate statistical significance for the pairwise differences: *** 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 A1.6), and order applications are sent in. Names are randomly assigned and independent from the above.

A1.2 Name

The full names used in this study are reported in Table A1. Additional information about the first names used in this study, where some imply the applicant is male and others female, are provided in Table A2. 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).

Additional information about the last names used in this study are provided in Table A3. 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 A1. 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).

In this study, I assume that employers use applicant first names to infer sex. While this is obvious for applicants who do not disclose pronouns, it is less clear for applicants who disclose "they/them" pronouns. However, there is supporting evidence: in 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. Further, Eames (2025) finds that, consistent with presumably cisgender applicants, nonbinary applicants with female-sounding names experience sex-based discrimination in male-dominated occupations and those with male-sounding names experience sex-based discrimination in female-dominated and mixed occupations. Together, this evidence indicates that employers likely use first names to infer sex.

A1.3 Summary

A "summary" is a brief, typically one-sentence objective or summary statement that may be included at the top of a resume. An example of a summary input for applicants applying as an administrative assistant is "To secure a position with a well-established organization with a stable environment that will lead to a lasting relationship." Summaries are occupation-specific, and each occupation randomizes across one of four summary inputs (or no summary). The majority (67%) of resumes in this study 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 slightly adjusted (to ensure generalizability).

A1.4 Education

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

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

For resumes assigned post-secondary education, schools and concentrations are occupation-specific. For each geography and occupation, education background information was scraped from the large job board for workers currently holding the occupation of interest: 20 who had an Associate's degree and 20 who had a Bachelor's degree.[22] 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.

A1.5 Work Experience

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

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

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

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

To identify the occupation-specific set of 33 work experience inputs outside of the occupation of interest, data was scraped from the resumes of real job seekers on the large job board website. For each geography and occupation, resume data was scraped from 150 resumes of applicants currently holding that occupation[23]. In total, 11,705 observations were collected, where each observation includes the last three positions listed on the resume. Using this

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

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.[24] 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.

A1.6 Resume Formatting

Two resume formats are used, which are designed to look as different from each other as possible (different font, different ordering of resume categories, different style, etc.). Once generated, resumes are adjusted as needed (by changing font size or margin width) to ensure

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

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 Additional Analyses

A2.1 Variable Definitions

Table A4 reports a detailed description of all variables included in the vector of resume controls (X_i). Table A5 reports a detailed description of all variables included in the vector of job posting controls (Z_j). Table A6 reports a detailed description of all interaction variables included in the vector of interaction variables (I).

A2.2 Balance Table

Tables A7 and A8 show resume characteristics, application timing, occupation, and CBSA for the control group (applicants who do not disclose pronouns) and both treatment arms (applicants who disclose nonbinary "they/them" pronouns and binary "he/him" or "she/her" pronouns congruent with name-implied sex). Results indicate that there is strong balance across attributes, which is unsurprising given that resumes were randomly generated. Resumes with no pronouns were slightly less likely to include a summary statement (see Section A1.3), and resumes with binary pronouns were slightly less likely to be used to apply to cashier positions.

A2.3 Additional Summary Statistics

Table A9 reports positive employer response rates and Chi-Squared test results by subgroup.

A2.4 Heterogeneous Discrimination Estimates

Tables A12 and A13 report full regression results from equation (3) that are shown in Figure 2 in the main paper.

A2.5 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.

To apply the Neumark's method using a heteroskedastic logistic model rather than the heteroskedastic probit model Neumark uses, marginal effects can be similarly disaggregated as follows. Note that in this brief section of the Appendix, I am using mathematical notation consistent with Neumark (2012)—this does not apply to the rest of the paper. As in Neumark (2012), consider a model with generic notation, where the latent variable $Y^* = P(Y = 1)$ depends on a vector of variables S (indexed by k) with coefficients ψ, and the variance ε depends on a vector of variables T with coefficients θ. That is:

$$Var(\varepsilon) = [\exp(T\theta)]^2$$

With the elements of T arranged such that the kth element is S_k, then the overall partial derivative of $P(Y = 1)$ with respect to S_k is:

$$\frac{\partial P(Y=1)}{\partial S_k} = \frac{\left(\dfrac{\psi_k - X'\psi \cdot \theta_k}{\exp\left(T'\theta\right)}\right) \cdot \exp\left(\dfrac{-X'\psi}{\exp\left(T'\theta\right)}\right)}{\left[1 + \exp\left(\dfrac{-X'\psi}{\exp\left(T'\theta\right)}\right)\right]^2} \tag{4}$$

The level part is then:

$$\frac{\left(\dfrac{\psi_k}{\exp\left(T'\theta\right)}\right) \cdot \exp\left(\dfrac{-X'\psi}{\exp\left(T'\theta\right)}\right)}{\left[1 + \exp\left(\dfrac{-X'\psi}{\exp\left(T'\theta\right)}\right)\right]^2} \tag{4'}$$

While the variance part is:

$$\frac{\left(\dfrac{-X'\psi \cdot \theta_k}{\exp\left(T'\theta\right)}\right) \cdot \exp\left(\dfrac{-X'\psi}{\exp\left(T'\theta\right)}\right)}{\left[1 + \exp\left(\dfrac{-X'\psi}{\exp\left(T'\theta\right)}\right)\right]^2} \tag{4''}$$

Results are presented in Table A11; I referenced code from Neumark et al. (2016) when generating. Results show that the unbiased discrimination estimate against applicants who disclose "they/them" pronouns is 5.6 percentage points and statistically significant at the 5% level; there is no evidence that the identifying assumption is violated. There is insufficient power to decompose discrimination from the act of pronoun disclosure generally and from an applicant's nonbinary gender identity separately into a levels and variance estimate.

A2.6 Testing for Detection Risk

Detection risk is a standard concern in correspondence studies: employers may realize an experiment is underway (or simply suspect something unusual). If that occurs, discrimination estimates are typically biased toward zero—either because employers inflate responses to treated applicants (due to social desirability bias) or because they stop contacting any applicants who look "off," both of which attenuate measured gaps (Balfe et al. 2023).

One diagnostic is to compare responses for treated applicants sent first versus second. If detection is present, treated applications sent second should receive higher responses, in line with Balfe et al. (2023). I estimate the following logistic regression model:

$$\log\left(\frac{p_{iocj}}{1-p_{iocj}}\right) = \gamma_1 P_i + \lambda_1 NB_i + \xi SF_i + \gamma_2[P_i \cdot SF_i] + \lambda_2[NB_i \cdot SF_i] + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj} \tag{4}$$

where variables are defined as in (1); SF_i is an indicator that equals 1 if application i was sent first within vacancy j. The vector X_i aguments baseline controls with days since posting at the time of application and its square, since earlier applications may receive greater attention and later ones may arrive after the effective decision window. The coefficient ξ captures the order effect for control applicants; γ_2 and λ_2 test whether treatment effects differ by order—detection would imply $\gamma_2 < 0$ and $\lambda_2 < 0$. Independent of treatment, a stopping-rule mechanism could generate a positive general order effect: $\xi > 0$ is plausible if employers stop considering additional applicants after assembling a target short-list or meeting a target pool, a process to which the first applicant my contribute.

Table A14 shows no evidence of detection. Among controls, first-sent applications receive slightly more positive responses than second-sent ones, but the difference is not statistically robust and disappears in the preferred specification (column 4). For treated applications, sending second does not raise response rates: the interaction terms are insignificant across all specifications and the corresponding coefficients are close to zero, again inconsistent with detection.

Results are reported in Table A14, and do not support detection. Most importantly, for treated applications, sending second rather than first does not increase positive responses: the interaction terms are insignificant across specifications and the point estimates are near zero. Less important is differences among control applications. Among controls, first-sent applications receive slightly more positive responses than second-sent ones; but, the difference is only statistically significant at the 10% level in the specifications one and two, and is not statistically significant in the preferred specification (column 4).

A2.7 Sex-Based Discrimination

Because applicants are randomly assigned male- or female-sounding names, this design also identifies sex-based discrimination. Historically, women have faced broad labor-market disadvantages; recent research shows that the direction of sex-based discrimination is occupation-specific. In particular, a consistent finding is that women are penalized in male-dominated occupations, whereas men are penalized in female-dominated occupations (Riach and Rich 2006; Yavorsky 2019; Cortina et al. 2021).

I estimate discrimination against applicants with female-sounding names in male-dominated occupations, and with male-sounding names in female-dominated and mixed occupations, via the following logistic regression:

$$\log\left(\frac{p_{iocj}}{1-p_{iocj}}\right) = \gamma P_i + \lambda NB_i + \varphi F_i^{MD} + \kappa M_i^{FD,M} + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj} \quad (5)$$

where F_i^{MD} equals 1 if the applicant has a female-sounding name and is applying in a male-dominated occupation and $M_i^{FD,M}$ equals 1 if the applicant has a male-sounding name and is applying in a femald-dominated or mixed occupation.[25]

Table A14 reports the results of equation (5) above. Results are consistent with the existing literature: applicants with female-sounding names are penalized in male-dominated occupations, and applicants with male-sounding names are penalized in female-dominated and mixed occupations. These estimates serve as benchmarks for the discrimination identified against nonbinary applicants. For additional information including intersectional effects—when applicants are nonbinary and their names imply the sex disadvantaged in that occupation—see Eames (2025).

[25] Applicant sex is perfectly collinear with variables $F_i^{MD}, M_i^{FD,M}, \eta_o$ and is thus excluded.

A3 Alternative Specifications

Table A16 reports average discrimination estimates from equation (1) and originally reported in Table 5 in the main paper, for each alternative specification listed below. Tables A17 and A18 report heterogeneous discrimination estimates by CBSA politics and posted wage range respectively, from equation (3), for each alternative specification listed below. Results are consistent with those presented in the main paper.

A3.1 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). I also consider a second version replacing occupation and city fixed effects (η_o, δ_c) with job posting fixed effects (θ_j):

$$y_{ij} = \gamma P_i + \lambda NB_i + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj} \tag{1'}$$

$$y_{ij} = \gamma_1 P_i + [P_i \cdot I']\gamma_2 + \lambda_1 NB_i + [NB_i \cdot I']\lambda_2 + X_i'\beta_1 + Z_j'\beta_2 + I'\beta_3 + \eta_o + \delta_c + \varepsilon_{iocj} \tag{3'}$$

A3.2 Weighted Observations

Following Solon et al. (2015) and Neumark et al. (2019b), I apply weights to make the experimental data more representative of the actual distribution of hires across occupations. Because the data collection process involved deliberately balancing application counts across occupations and CBSAs, some occupation-CBSA pairs are over- or under-sampled relative to actual hiring volumes. Table A19 illustrates this by comparing the share of applications to actual hiring volume within each occupation-geography pair. Actual hiring volumes by NAICS code are sourced from Quarterly Workforce Indicators (U.S. Census Bureau 2023b), and the percent of each NAICS code employed by in each occupation SOC Code is sourced from Occupational Employment and Wage Statistics (U.S. Bureau of Labor Statistics 2025). Estimated new hires per occupation are calculated by multiplying industry-level hires by the occupation's employment share within each NAICS code, then summing across all industries.[26]

I implement two weighting approaches, with weights listed in Table A20. In the first (weights reported in Panel A), I generate weights to adjust the occupation-level application shares across geographies to match observed hiring shares—each occupation. Weights are thus calculated as the ratio of each occupation's actual hiring share to its share of applications. In the second approach (Panel B), I generate weights to match occupation shares within rather than across CBSAs. When analyzing geographic heterogeneity—particularly differences between Democratic and Republican CBSAs—approach one is more appropriate, as it avoids conflating political effects with differences in how observations are weighted across regions.

A3.3 Alternative Positive Employer Response: Less Strict

Per the pre-analysis plan, in this study, "employer response [is] viewed as 'positive' if they contact the applicant and either offer an interview or request the applicant contact them" (Eames 2023). I consider an alternative definition that is less strict: employer responses is 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.

[26] I match SOC codes to occupations as follows. Code 43-6010 is Administrative Assistant; 51-200 is Assembler; 51-3010 is Baker; 41-2010 is Cashier; 31-1100 is Certified Nursing Assistant; 47-2040, 47-2050, 47-2060, 47-2070, 47-2080, 47-2180 are Construction Worker; 35-2010 is Cook; 37-2012 is Housekeeper; 37-2011 is Janitor; 37-3011 is Landscaper; 43-4170, 43-4080, 43-4050 are Receptionist; 41-2030, 41-2020 are Retail Sales; 35-3030 is Server; 53-3030 and 53-3090 are Truck Driver; 53-7062, 53-7064, 53-7065 are Warehouse Worker.

A3.4 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 positive only 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.

A3.5 Omit Observations with Blank Responses

As a rule, RAs did not respond to application questions where answers could not be found in the resume—see Section 1.5 in the main paper for more information. In some cases, blank answers are expected—for example when applicants were asked whether they had been referred by a current employee (e.g., "If yes, please provide their name; if not, leave blank"). However, in other cases, employers may expect a response—for example, "how would you describe your teamwork style?" or "why are you interested in this job?" In these cases, blank responses may signal something about the applicant—5.6% of applications have such blank answers.[27] As a robustness check, I run equation (3) omitting these 5.6% of observations.

A3.6 Include Additional Interaction Controls

This applies to heterogeneous discrimination estimates only.

Hull et al. (1992) and Yzerbyt et al. (2004) show that, when testing for interaction effects between a predictor and a covariate, there is elevated false positive risk when the predictor and covariate are correlated or when their interaction is associated with the dependent variable. To address this, an alternative version of equation (3") is run including additional interactions between predictors (NB_i, B_i) and interaction variables (I, a vector containing

[27] While this information was generally recorded, it was not originally planned to be used in analysis. As such, a small number of cases may have gone undocumented, though any such instances are expected to be rare.

k variables), and controls (X_i, Z_j) and interaction variables. That is:

$$\log\left(\frac{p_{iocj}}{1-p_{iocj}}\right) = \gamma_1 P_i + [P_i \cdot I']\gamma_2 + \lambda_1 NB_i + [NB_i \cdot I']\lambda_2 + X_i'\beta_1 + Z_j'\beta_2 + I'\beta_3$$
$$+ [P_i \cdot X_i']\beta_4 + [P_i \cdot Z_j']\beta_5 + [NB_i \cdot X_i']\beta_6 + [NB_i \cdot Z_j']\beta_7 \quad (3\text{''})$$
$$+ [I' \cdot X_i']\beta_8 + [I' \cdot Z_j']\beta_9 + \eta_o + \delta_c + \varepsilon_{iocj}$$

A3.7 Replace Republican CBSA Indicator with Republican County Indicator

This applies to heterogeneous discrimination estimates by CBSA politics only.

For this analysis, one additional specification is included: the Republican CBSA indicator is replaced with a Republican County indicator, which equals 1 if the county had more Republican than Democratic votes in the 2020 Presidential election. Although county and CBSA political classifications largely align, there are some discrepancies. In Republican CBSAs, 87% of applications were sent to job postings in Republican counties, while 13% were in Democratic counties. In Democratic CBSAs, 94% of applications went to Democratic counties, with the remaining 6% in Republican counties.

A3.8 Replace Wage Range Indicator with Alternative Version

In the main paper, I generate an indicator variable which equals 1 if the employer lists a wide wage range in their job posting, where I define "wide" as being above the occupation-CBSA average. Here, I consider an alternative definition: if there is no wage range at all (i.e., there is a single posted wage) then the range is considered narrow; if there exists a wage range, it is considered wide.

Importantly, the vast majority of job postings include wage information: 93.6% of the data sample. As such, selection issues regarding which firms disclose wage information are unlikely to matter.

Appendix Tables and Figures

Table A1: 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 1.5. 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 racially ambiguous as intended.

Table A2: First Names

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

Note: rank is the rank of name popularity among babies born in the 1990s (where 1 is the most popular name); count is the count of babies born in the 1990s with that name; data is sourced from U.S. Social Security (2023). Data on name association scores (warmth and competency) is sourced from Newman et al. (2018). 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 racially ambiguous as intended.

Table A3: Last Names

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

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

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

Table A4: Resume Characteristics (X_i Control Variables)

Variable	Type	Description
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
Posting lag	Discrete	Equals the number of days between the job was posted and the first application was sent
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"
Prior most common	Discrete	Equals the years of "most common" experience, omitting most recent experience
Prior most 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 A1.5 in the Online 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. 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 A5: Job Posting Characteristics (Z_j Control Variables)

Variable	Type	Description
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
Standardized wage	Continuous	The midpoint of estimated income, standardized within occupation and CBSA
Standardized wage^2	Continuous	Above squared
Standardized wage range	Continuous	The difference between the upper and lower estimated income bounds, standardized within occupation and CBSA
Standardized wage range^2	Continuous	Above squared
Missing estimated income	Indicator	Equals 1 if the job posting did not include an associated income range

Table A6: Interaction Variables

Variable	Description
Republican CBSA	Equals 1 if the job is located in a Republican CBSA (Spokane, WA; Provo, UT; Colorado Springs, CO)
Republican County	Equals 1 if the job is located in a county where Republicans received more votes than Democrats in the 2020 Presidential election
High Wage	Equals 1 if standardized wage is above zero (i.e., the midpoint of estimated income is above average within the occupation and CBSA)
Wide Wage Range	Equals 1 if standardized wage range is above zero (i.e., the difference between the upper and lower estimated income bounds is above average within the occupation and CBSA)
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)

Table A7: Balance Table (1 of 2)

Attribute	NP	NB	NB - NP	B	B - NP
Panel A: Resume Characteristics					
Implied Female (%)	0.500	0.494	-0.006	0.512	0.013
	(0.001)	(0.001)		(0.002)	
Worked in high school (%)	0.283	0.275	-0.009	0.288	0.005
	(0.001)	(0.001)		(0.001)	
Includes extra summary section (%)	0.316	0.336	0.020 *	0.344	0.028 *
	(0.001)	(0.001)		(0.002)	
Highest education level: GED (%)	0.090	0.091	0.001	0.088	-0.002
	(0.000)	(0.001)		(0.001)	
Highest education level: Associate's (%)	0.082	0.079	-0.002	0.086	0.004
	(0.000)	(0.001)		(0.001)	
Highest education level: Bachelor's (%)	0.097	0.100	0.003	0.091	-0.006
	(0.000)	(0.001)		(0.001)	
Attended a low-score high school (%)	0.315	0.311	-0.004	0.325	0.009
	(0.001)	(0.001)		(0.002)	
Attended a high-score high school (%)	0.306	0.313	0.007	0.291	-0.015
	(0.001)	(0.001)		(0.001)	
Years of relevant experience (Avg.)	1.065	1.061	-0.004	1.072	0.007
	(0.017)	(0.021)		(0.030)	
Most recent experience is "relevant" (%)	0.244	0.242	-0.002	0.249	0.004
	(0.001)	(0.001)		(0.001)	
Most recent experience is "most common" (%)	0.129	0.116	-0.013	0.120	-0.009
	(0.001)	(0.001)		(0.001)	
Prior experience is "most common" (%)	0.344	0.360	0.016	0.364	0.020
	(0.001)	(0.001)		(0.002)	
Panel B: Application Timing					
Application is sent first (%)	0.504	0.489	-0.014	0.504	0.000
	(0.001)	(0.001)		(0.002)	
Resume lag (hours between first and second) (Avg.)	19.088	19.302	0.214	19.195	0.107
	(0.121)	(0.146)		(0.213)	
Posting lag (days between posting and first resume) (Avg.)	0.763	0.759	-0.005	0.773	0.010
	(0.014)	(0.017)		(0.025)	
Panel C: Job Posting Characteristics					
Application volume (Avg.)	51.217	49.821	-1.396	54.133	2.916
	(1.323)	(1.589)		(2.386)	
Standardized wage (Avg.)	0.000	0.004	0.004	-0.009	-0.009
	(0.015)	(0.019)		(0.026)	
Standardized wage range (Avg.)	0.000	-0.009	-0.009	0.019	0.019
	(0.015)	(0.019)		(0.026)	

Note: The percent of resumes containing each attribute (%) or the average across resumes (Avg.) is reported; standard errors are reported in parentheses. Column labels denote treatment or control group: NP is no pronouns, NB is nonbinary "they/them" pronouns, and B is binary "he/him" or "she/her" pronouns congruent with name-implied sex. For more information on variable definitions, see Tables A4 and A5. The difference between treatment and control groups is also reported, and stars indicate statistical significance: * 10%, ** 5%, *** 1% levels.

Table A8: Balance Table (2 of 2)

Attribute	NP	NB	NB - NP	B	B - NP
Panel D: Percent of Resumes by Occupation					
Administrative Assistant (%)	0.055	0.055	0.000	0.055	0.000
	(0.000)	(0.000)		(0.001)	
Assembler (%)	0.042	0.039	-0.003	0.047	0.006
	(0.000)	(0.000)		(0.001)	
Baker (%)	0.023	0.024	0.001	0.021	-0.002
	(0.000)	(0.000)		(0.000)	
Cashier (%)	0.044	0.052	0.007	0.029	-0.015 **
	(0.000)	(0.000)		(0.000)	
Certified Nursing Assistant (%)	0.096	0.097	0.001	0.093	-0.003
	(0.000)	(0.001)		(0.001)	
Construction Worker (%)	0.054	0.052	-0.002	0.057	0.003
	(0.000)	(0.000)		(0.001)	
Cook (%)	0.087	0.084	-0.003	0.092	0.005
	(0.000)	(0.001)		(0.001)	
Housekeeper (%)	0.057	0.056	-0.001	0.060	0.003
	(0.000)	(0.000)		(0.001)	
Janitor (%)	0.054	0.060	0.006	0.043	-0.012
	(0.000)	(0.000)		(0.001)	
Landscaper (%)	0.053	0.054	0.000	0.053	-0.001
	(0.000)	(0.000)		(0.001)	
Receptionist (%)	0.075	0.075	0.000	0.076	0.001
	(0.000)	(0.001)		(0.001)	
Retail Sales (%)	0.125	0.124	-0.002	0.129	0.003
	(0.001)	(0.001)		(0.001)	
Server (%)	0.050	0.049	-0.001	0.053	0.003
	(0.000)	(0.000)		(0.001)	
Truck Driver (%)	0.099	0.099	0.000	0.100	0.001
	(0.000)	(0.001)		(0.001)	
Warehouse Worker (%)	0.084	0.081	-0.004	0.091	0.007
	(0.000)	(0.001)		(0.001)	
Panel E: Percent of Resumes by CBSA					
Seattle, WA (%)	0.167	0.168	0.001	0.164	-0.003
	(0.001)	(0.001)		(0.001)	
Spokane, WA (%)	0.165	0.170	0.004	0.157	-0.009
	(0.001)	(0.001)		(0.001)	
Salt Lake City, UT (%)	0.168	0.164	-0.004	0.176	0.008
	(0.001)	(0.001)		(0.001)	
Provo, UT (%)	0.168	0.171	0.003	0.160	-0.007
	(0.001)	(0.001)		(0.001)	
Denver, CO (%)	0.167	0.164	-0.003	0.174	0.007
	(0.001)	(0.001)		(0.001)	
Colorado Springs, CO (%)	0.165	0.163	-0.002	0.170	0.004
	(0.001)	(0.001)		(0.001)	

Note: The percent of resumes containing each attribute (%) is reported; standard errors are reported in parentheses. Column labels denote treatment or control group: NP is no pronouns, NB is nonbinary "they/them" pronouns, and B is binary "he/him" or "she/her" pronouns congruent with name-implied sex. The difference between treatment and control groups is also reported, and stars indicate statistical significance: * 10%, ** 5%, *** 1% levels.

Table A9: Differences in Positive Employer Response by Group

	Positive Employer Response						Sample Size		
CBSA	NP	NB	NB - NP	B	B - NP	NB - B	NP	NB	B
Panel A: Overall Results									
All Observations	0.313	0.258	-0.055 ***	0.294	-0.019	-0.036 **	3,985	2695	1290
			(0.011)		(0.015)	(0.015)			
Panel B: by Geographic Politics									
Democratic CBSA	0.321	0.283	-0.038 **	0.311	-0.010	-0.028	1999	1337	662
			(0.016)		(0.021)	(0.022)			
Republican CBSA	0.305	0.233	-0.071 ***	0.275	-0.029	-0.042 **	1986	1358	628
			(0.015)		(0.021)	(0.021)			
Democratic County	0.321	0.283	-0.038 **	0.311	-0.010	-0.028	1999	1337	662
			(0.016)		(0.021)	(0.022)			
Republican County	0.309	0.235	-0.074 ***	0.278	-0.032	-0.043 **	1853	1255	598
			(0.016)		(0.021)	(0.022)			
Panel C: by Job Posting Wage									
Low Wage	0.354	0.293	-0.061 ***	0.316	-0.038 *	-0.023	2368	1586	782
			(0.015)		(0.019)	(0.020)			
High Wage	0.252	0.204	-0.048 ***	0.267	0.014	-0.062 **	1360	936	424
			(0.018)		(0.024)	(0.025)			
Narrow Wage Range	0.344	0.269	-0.075 ***	0.321	-0.023	-0.052 ***	2352	1611	741
			(0.015)		(0.020)	(0.020)			
Wide Wage Rang	0.270	0.245	-0.026	0.262	-0.008	-0.018	1376	911	465
			(0.019)		(0.024)	(0.025)			
Panel D: by Occupation Category									
Male-Dominated	0.289	0.235	-0.054 ***	0.277	-0.011	-0.042 *	1376	932	444
			(0.018)		(0.024)	(0.025)			
Non-Dominated	0.330	0.265	-0.065 ***	0.299	-0.031	-0.034	1305	864	441
			(0.020)		(0.025)	(0.026)			
Female-Dominated	0.321	0.276	-0.045 **	0.306	-0.015	-0.030	1304	899	405
			(0.020)		(0.026)	(0.027)			
High Customer-Facing	0.304	0.244	-0.059 ***	0.284	-0.020	-0.039	1176	806	370
			(0.020)		(0.027)	(0.028)			
Medium Customer-Facing	0.293	0.260	-0.034	0.265	-0.028	-0.005	1186	786	400
			(0.020)		(0.026)	(0.027)			
Low Customer-Facing	0.334	0.267	-0.066 ***	0.323	-0.011	-0.056 **	1623	1103	520
			(0.018)		(0.024)	(0.024)			
Panel E: by Experience									
No Relevant Experience	0.261	0.213	-0.048 ***	0.247	-0.014	-0.034	1680	1146	534
			(0.016)		(0.022)	(0.022)			
1+ Years Relevant Experience	0.351	0.292	-0.059 ***	0.327	-0.024	-0.035 *	2305	1549	756
			(0.015)		(0.020)	(0.021)			

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. Column "NB - B" reports the difference in response rates between applicants who disclose nonbinary pronouns and those who disclose binary 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 A10: County Differences in Democratic and Republican CBSAs

	County-Level Mean		
Variable	Democratic CBSA	Republican CBSA	Difference
Panel A: Counties in all U.S. CBSAs			
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)
Panel B: Counties in the six study CBSAs			
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 (2023a), land square miles from from TIGERweb U.S. Census Bureau (2020), income and education data from US Deparmtnet of Agriculture (2023), and religious congregation data from US Religious Census (2020). Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table A11: Heteroskedastic Logistic Discrimination Estimates
(Neumark's Bias Correction)

	Pronoun Disclosure (γ)	Nonbinary Identity (λ)	Total "they/them" ($\gamma + \lambda$)
Panel A: Logistic coefficient estimates			
Coefficient Estimate	-0.017	-0.038**	-0.055***
	(0.011)	(0.015)	(0.008)
Panel B: Heteroskedastic logistic coefficient estimates			
Total Estimate	-0.017	-0.040**	-0.056***
	(0.013)	(0.016)	(0.008)
Levels Estimate	-0.031	-0.022	-0.053 **
	(0.032)	(0.042)	(0.021)
Variance Estimate	0.014	-0.018	-0.003
	(0.031)	(0.039)	(0.020)
Panel C: Tests			
Overidentification test p-value (X_i coefficient ratios are equal for treatment and control)	0.994	0.896	0.856
Standard deviation of unobservables (treatment / control)	0.911	1.078	0.982
S.D. test p-value (ratio of standard deviations = 1)	0.601	0.676	0.888
Panel D: Regression Controls			
Resume Controls	✓	✓	✓
Job Posting Controls			
Occupation Fixed Effects	✓	✓	✓
CBSA Fixed Effects	✓	✓	✓
Observations	7,970	7,970	7,970

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 and fixed effects; Panel B is derived from a heteroskedastic version of the same logistic regression and decomposed as 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. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table A12: Heterogeneous Discrimination Estimates (1 of 2)

	(1) by CBSA Politics I: Republican	(3) by Experience I: 1+ Years Relevant	(4) by Wage I: High	(5) by Wage Range I: Wide
Panel A: Reference Group Discrimination Estimates				
Pronoun Disclosure (γ_1)	-0.010 (0.016) [-0.041, 0.021]	-0.022 (0.019) [-0.059, 0.015]	-0.031** (0.015) [-0.060, -0.002]	-0.019 (0.015) [-0.048, 0.011]
Nonbinary Gender Identity (λ_1)	-0.026 (0.021) [-0.066, 0.014]	-0.036 (0.024) [-0.083, 0.011]	-0.026 (0.019) [-0.063, 0.010]	-0.052*** (0.019) [-0.090, -0.015]
Total "they/them" Disclosure ($\gamma_1 + \lambda_1$)	-0.036*** (0.011) [-0.057, -0.014]	-0.058*** (0.013) [-0.084, -0.033]	-0.057*** (0.010) [-0.078, -0.037]	-0.071*** (0.011) [-0.092, -0.050]
Panel B: Interaction Group Discrimination Estimates				
Pronoun Disclosure × I_1 (γ_2)	-0.014 (0.023) [-0.060, 0.031]	0.009 (0.025) [-0.040, 0.057]	0.050* (0.027) [-0.002, 0.102]	0.010 (0.025) [-0.039, 0.060]
Nonbinary Gender Identity × I_1 (λ_2)	-0.025 (0.029) [-0.083, 0.032]	-0.003 (0.031) [-0.064, 0.058]	-0.047 (0.031) [-0.108, 0.014]	0.034 (0.034) [-0.033, 0.101]
Total "they/them" Disclosure × I_1 ($\gamma_2 + \lambda_2$)	-0.040** (0.016) [-0.071, -0.008]	0.006 (0.017) [-0.028, 0.039]	0.003 (0.017) [-0.030, 0.037]	0.044** (0.019) [0.008, 0.080]
Panel C: Specification Information				
Resume Controls	✓	✓	✓	✓
Job Posting Controls	✓	✓	✓	✓
Occupation Fixed Effects	✓	✓	✓	✓
CBSA Fixed Effects	✓	✓	✓	✓
Observations	7,970	7,970	7,970	7,970

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

Table A13: Heterogeneous Discrimination Estimates (2 of 2)

	(1) by Worker Sex Composition I_1: Male-Dominated I_2: Female-Dominated	(2) by Customer-Facing Level I_1: Low I_2: High
Panel A: Reference Group Discrimination Estimates		
Pronoun Disclosure (γ_1)	-0.024 (0.020) [-0.063, 0.015]	-0.030 (0.022) [-0.072, 0.012]
Nonbinary Gender Identity (λ_1)	-0.038 (0.025) [-0.088, 0.012]	-0.004 (0.028) [-0.058, 0.051]
Total "they/them" Disclosure ($\gamma_1 + \lambda_1$)	-0.062*** (0.014) [-0.090, -0.034]	-0.034** (0.015) [-0.063, -0.005]
Panel B: Interaction Group 1 Discrimination Estimates		
Pronoun Disclosure × I_1 (γ_2)	0.014 (0.028) [-0.041, 0.070]	0.020 (0.029) [-0.036, 0.076]
Nonbinary Gender Identity × I_1 (λ_2)	-0.010 (0.036) [-0.081, 0.061]	-0.051 (0.034) [-0.117, 0.015]
Total "they/them" Disclosure × I_1 ($\gamma_2 + \lambda_2$)	0.005 (0.020) [-0.034, 0.044]	-0.031* (0.018) [-0.066, 0.004]
Panel C: Interaction Group 2 Discrimination Estimates		
Pronoun Disclosure × I_2 (γ_3)	0.007 (0.030) [-0.051, 0.065]	0.019 (0.032) [-0.044, 0.081]
Nonbinary Gender Identity × I_2 (λ_3)	0.010 (0.038) [-0.065, 0.084]	-0.044 (0.037) [-0.117, 0.029]
Total "they/them" Disclosure × I_2 ($\gamma_3 + \lambda_3$)	0.017 (0.020) [-0.023, 0.057]	-0.025 (0.020) [-0.064, 0.014]
Panel D: Specification Information		
Resume Controls	✓	✓
Job Posting Controls	✓	✓
Occupation Fixed Effects	✓	✓
CBSA Fixed Effects	✓	✓
Observations	7,970	7,970

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

Table A14: Detection Test

	(1)	(2)	(3)	(4)
Panel A: Coefficient Estimates (Average Treatment Effects)				
Application Sent First (ξ)	0.027*	0.027*	0.023	0.023
	(0.016)	(0.016)	(0.016)	(0.016)
	[-0.004, 0.059]	[-0.004, 0.058]	[-0.009, 0.055]	[-0.008, 0.055]
Pronoun Disclosure (γ_1)	-0.010	-0.012	-0.012	-0.014
	(0.021)	(0.020)	(0.020)	(0.020)
	[-0.050, 0.030]	[-0.052, 0.028]	[-0.051, 0.028]	[-0.053, 0.025]
Nonbinary Gender Identity (λ_1)	-0.040*	-0.040*	-0.043**	-0.041**
	(0.021)	(0.021)	(0.021)	(0.021)
	[-0.082, 0.002]	[-0.082, 0.002]	[-0.084, -0.001]	[-0.083, 0.000]
Total "they/them" Disclosure ($\gamma_1 + \lambda_1$)	-0.050***	-0.052***	-0.054***	-0.055***
	(0.016)	(0.016)	(0.015)	(0.015)
	[-0.082, -0.019]	[-0.083, -0.021]	[-0.084, -0.024]	[-0.085, -0.025]
Panel B: Interaction Effects				
Application Sent First × Pronoun Disclosure (γ_2)	-0.017	-0.013	-0.010	-0.006
	(0.033)	(0.032)	(0.032)	(0.032)
	[-0.081, 0.047]	[-0.076, 0.051]	[-0.074, 0.053]	[-0.069, 0.057]
Application Sent First × Nonbinary Gender Identity (λ_2)	0.009	0.009	0.009	0.007
	(0.031)	(0.031)	(0.031)	(0.031)
	[-0.052, 0.070]	[-0.052, 0.070]	[-0.052, 0.070]	[-0.053, 0.067]
Application Sent First × Total "they/them" Disclosure ($\gamma_2 + \lambda_2$)	-0.008	-0.004	-0.001	0.001
	(0.028)	(0.027)	(0.028)	(0.027)
	[-0.063, 0.047]	[-0.057, 0.050]	[-0.055, 0.053]	[-0.052, 0.054]
Panel C: Specification Information				
Resume Controls		✓		✓
Job Posting Controls		✓		✓
Occupation Fixed Effects			✓	✓
CBSA Fixed Effects			✓	✓
Observations	7,970	7,970	7,970	7,970

Notes: This table reports average marginal effects from the logistic model in equation (4). The dependent variable equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table A15: Sex-Based Discrimination Estimates

	(1) All Observations	(2) Control Observations Only
Panel A: Coefficient Estimates		
Female (in Male-Dominated Occupations)	-0.070***	-0.076***
	(0.019)	(0.023)
	[-0.108, -0.032]	[-0.121, -0.032]
Male (in Female-Dominated or Mixed Occupations)	-0.047***	-0.053***
	(0.015)	(0.017)
	[-0.075, -0.018]	[-0.086, -0.019]
Panel B: Specification Information		
Resume Controls	✓	✓
Job Posting Controls	✓	✓
Occupation Fixed Effects	✓	✓
CBSA Fixed Effects	✓	✓
Observations	7,970	3,985

Notes: This table reports average marginal effects from the logistic model in equation (5). The dependent variable equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1% level, ** 5% level, * 10% level.

Table A16: Average Discrimination Estimates—Robustness Checks

	(1) Baseline	(2) OLS 1	(3) OLS 2	(4) Weighted 1	(5) Weighted 2	(6) Less Restrictive	(7) More Restrictive	(8) Omit Blanks
Panel A: Discrimination Estimates (Average Treatment Effects)								
	-0.017	-0.018	-0.022**	-0.016	-0.013	-0.020	-0.005	-0.018
Disclose Any Pronouns (γ)	(0.012)	(0.012)	(0.011)	(0.012)	(0.013)	(0.012)	(0.011)	(0.012)
	[-0.040, 0.006]	[-0.041, 0.005]	[-0.043, -0.001]	[-0.040, 0.009]	[-0.038, 0.012]	[-0.043, 0.004]	[-0.026, 0.016]	[-0.042, 0.006]
	-0.038**	-0.037**	-0.030**	-0.039**	-0.044***	-0.034**	-0.043***	-0.033**
Disclose Nonbinary Pronouns (λ)	(0.015)	(0.015)	(0.013)	(0.016)	(0.016)	(0.015)	(0.014)	(0.015)
	[-0.068, -0.009]	[-0.066, -0.008]	[-0.056, -0.004]	[-0.071, -0.008]	[-0.076, -0.012]	[-0.064, -0.003]	[-0.070, -0.016]	[-0.063, -0.003]
	-0.055***	-0.055***	-0.052***	-0.055***	-0.056***	-0.053***	-0.048***	-0.051***
Combined ($\gamma + \lambda$)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)
	[-0.071, -0.039]	[-0.070, -0.039]	[-0.067, -0.037]	[-0.073, -0.037]	[-0.074, -0.039]	[-0.070, -0.037]	[-0.063, -0.032]	[-0.068, -0.034]
Panel B: Specification Information								
Resume Controls	✓	✓	✓	✓	✓	✓	✓	✓
Job Posting Controls	✓	✓	✓	✓	✓	✓	✓	✓
Occupation Fixed Effects	✓	✓		✓	✓	✓	✓	✓
CBSA Fixed Effects	✓	✓		✓	✓	✓	✓	✓
Job Posting Fixed Effects			✓					
Observations	7,970	7,970	7,970	7,970	7,970	7,970	7,970	7,552

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 A17: Heterogeneous Discrimination Estimates by Republican CBSA—Robustness Checks

	(1) Baseline	(2) County	(3) OLS 1	(4) OLS 2	(5) Weighted 1	(6) Weighted 2	(7) Less Restrictive	(8) More Restrictive	(9) Omit Blanks
Panel A: Reference Group Discrimination Estimates									
Pronoun Disclosure (γ_1)	-0.010	-0.007	-0.011	-0.011	-0.006	-0.005	-0.012	0.001	-0.011
	(0.016)	(0.016)	(0.017)	(0.014)	(0.017)	(0.017)	(0.017)	(0.014)	(0.016)
	[-0.041, 0.021]	[-0.038, 0.024]	[-0.043, 0.022]	[-0.039, 0.017]	[-0.039, 0.028]	[-0.039, 0.029]	[-0.044, 0.021]	[-0.028, 0.029]	[-0.043, 0.021]
Nonbinary Gender Identity (λ_1)	-0.026	-0.030	-0.027	-0.026	-0.027	-0.028	-0.025	-0.033*	-0.020
	(0.021)	(0.020)	(0.021)	(0.018)	(0.022)	(0.022)	(0.021)	(0.019)	(0.021)
	[-0.066, 0.014]	[-0.070, 0.009]	[-0.068, 0.015]	[-0.061, 0.009]	[-0.071, 0.016]	[-0.071, 0.015]	[-0.067, 0.017]	[-0.070, 0.004]	[-0.062, 0.021]
Total "they/them" Disclosure ($\gamma_1 + \lambda_1$)	-0.036***	-0.037***	-0.037***	-0.037***	-0.033***	-0.033***	-0.036***	-0.033***	-0.032***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)	(0.010)	(0.011)
	[-0.057, -0.014]	[-0.059, -0.016]	[-0.059, -0.015]	[-0.058, -0.016]	[-0.056, -0.010]	[-0.056, -0.010]	[-0.058, -0.015]	[-0.052, -0.013]	[-0.054, -0.009]
Panel B: Interaction Group Discrimination Estimates									
Pronoun Disclosure × I_1 (γ_2)	-0.014	-0.021	-0.015	-0.024	-0.020	-0.015	-0.017	-0.011	-0.014
	(0.023)	(0.024)	(0.024)	(0.021)	(0.025)	(0.025)	(0.024)	(0.021)	(0.024)
	[-0.060, 0.031]	[-0.069, 0.026]	[-0.062, 0.031]	[-0.065, 0.018]	[-0.069, 0.028]	[-0.064, 0.034]	[-0.064, 0.030]	[-0.052, 0.030]	[-0.061, 0.033]
Nonbinary Gender Identity × I_1 (λ_2)	-0.025	-0.018	-0.021	-0.007	-0.024	-0.032	-0.018	-0.021	-0.026
	(0.029)	(0.030)	(0.030)	(0.026)	(0.031)	(0.032)	(0.031)	(0.027)	(0.030)
	[-0.083, 0.032]	[-0.076, 0.040]	[-0.079, 0.038]	[-0.058, 0.044]	[-0.086, 0.037]	[-0.095, 0.030]	[-0.078, 0.042]	[-0.074, 0.032]	[-0.085, 0.033]
Total "they/them" Disclosure × I_1 ($\gamma_2 + \lambda_2$)	-0.040**	-0.040**	-0.036**	-0.030**	-0.045***	-0.047***	-0.035**	-0.032**	-0.040**
	(0.016)	(0.018)	(0.016)	(0.015)	(0.017)	(0.017)	(0.016)	(0.015)	(0.017)
	[-0.071, -0.008]	[-0.074, -0.005]	[-0.067, -0.005]	[-0.061, 0.000]	[-0.079, -0.011]	[-0.081, -0.013]	[-0.067, -0.003]	[-0.061, -0.003]	[-0.072, -0.008]
Panel C: Specification Information									
Resume Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Job Posting Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occupation Fixed Effects	✓	✓	✓		✓	✓	✓	✓	✓
CBSA Fixed Effects	✓	✓	✓		✓	✓	✓	✓	✓
Job Posting Fixed Effects				✓					
Observations	7,970	7,970	7,970	7,970	7,970	7,970	7,970	7,970	7522

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 A18: Heterogeneous Discrimination Estimates by Wage Range—Robustness Checks

	(1) Baseline	(2) Range > 0	(3) OLS 1	(4) OLS 2	(5) Weighted 1	(6) Weighted 2	(7) Less Restrictive	(8) More Restrictive	(9) Omit Blanks
Panel A: Reference Group Discrimination Estimates									
Pronoun Disclosure (γ_1)	-0.019	-0.025	-0.021	-0.033**	-0.013	-0.012	-0.018	-0.005	-0.026
	(0.015)	(0.021)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)	(0.014)	(0.016)
	[-0.048, 0.011]	[-0.066, 0.016]	[-0.053, 0.011]	[-0.062, -0.004]	[-0.045, 0.019]	[-0.044, 0.021]	[-0.048, 0.013]	[-0.032, 0.022]	[-0.056, 0.005]
Nonbinary Gender Identity (λ_1)	-0.052***	-0.049**	-0.053***	-0.036**	-0.058***	-0.063***	-0.054***	-0.055***	-0.040**
	(0.019)	(0.025)	(0.020)	(0.018)	(0.020)	(0.021)	(0.020)	(0.018)	(0.020)
	[-0.090, -0.015]	[-0.098, -0.001]	[-0.092, -0.013]	[-0.071, 0.000]	[-0.098, -0.018]	[-0.103, -0.022]	[-0.092, -0.015]	[-0.089, -0.020]	[-0.079, -0.002]
Total "they/them" Disclosure ($\gamma_1 + \lambda_1$)	-0.071***	-0.075***	-0.074***	-0.068***	-0.071***	-0.074***	-0.071***	-0.060***	-0.066***
	(0.011)	(0.014)	(0.011)	(0.010)	(0.012)	(0.012)	(0.011)	(0.010)	(0.011)
	[-0.092, -0.050]	[-0.102, -0.047]	[-0.095, -0.053]	[-0.089, -0.048]	[-0.094, -0.048]	[-0.097, -0.051]	[-0.092, -0.051]	[-0.079, -0.040]	[-0.087, -0.045]
Panel B: Interaction Group Discrimination Estimates									
Pronoun Disclosure × I_1 (γ_2)	0.010	0.013	0.013	0.037*	0.000	0.003	-0.001	0.003	0.023
	(0.025)	(0.026)	(0.025)	(0.022)	(0.027)	(0.027)	(0.026)	(0.023)	(0.026)
	[-0.039, 0.060]	[-0.038, 0.064]	[-0.036, 0.062]	[-0.005, 0.080]	[-0.053, 0.053]	[-0.050, 0.057]	[-0.052, 0.050]	[-0.042, 0.049]	[-0.029, 0.074]
Nonbinary Gender Identity × I_1 (λ_2)	0.034	0.019	0.035	-0.001	0.042	0.043	0.052	0.031	0.017
	(0.034)	(0.032)	(0.031)	(0.027)	(0.037)	(0.037)	(0.035)	(0.032)	(0.034)
	[-0.033, 0.101]	[-0.044, 0.082]	[-0.027, 0.096]	[-0.054, 0.053]	[-0.030, 0.113]	[-0.030, 0.116]	[-0.017, 0.121]	[-0.033, 0.094]	[-0.051, 0.084]
Total "they/them" Disclosure × I_1 ($\gamma_2 + \lambda_2$)	0.044**	0.032*	0.048***	0.037**	0.042**	0.047**	0.051***	0.034*	0.039**
	(0.019)	(0.019)	(0.017)	(0.016)	(0.020)	(0.020)	(0.019)	(0.018)	(0.019)
	[0.008, 0.081]	[-0.005, 0.069]	[0.015, 0.080]	[0.005, 0.069]	[0.002, 0.081]	[0.006, 0.087]	[0.015, 0.088]	[-0.001, 0.069]	[0.003, 0.076]
Panel C: Specification Information									
Resume Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Job Posting Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occupation Fixed Effects	✓	✓	✓		✓	✓	✓	✓	✓
CBSA Fixed Effects	✓	✓	✓		✓	✓	✓	✓	✓
Job Posting Fixed Effects				✓					
Observations	7,970	7,970	7,970	7,970	7,970	7,970	7,970	7,970	7522

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 A19: New Hire versus Application Counts

Occupation	Seattle, WA	Spokane, WA	Salt Lake City, UT	Provo, UT	Denver, CO	Colorado Springs, CO
Panel A: Q2 2023 New Hire Counts per Occupation-CBSA Pair						
Construction Worker	6597 (8%)	1330 (9%)	3745 (10%)	1839 (11%)	5557 (7%)	1031 (6%)
Baker	509 (1%)	55 (0%)	177 (0%)	69 (0%)	331 (0%)	67 (0%)
Assembler	2736 (3%)	292 (2%)	1273 (3%)	496 (3%)	2025 (2%)	271 (2%)
Retail Sales	7118 (9%)	1304 (9%)	3427 (9%)	1495 (9%)	7756 (9%)	1472 (8%)
Cashier	3884 (5%)	660 (4%)	2010 (5%)	915 (6%)	4534 (5%)	1147 (6%)
Truck Driver	5469 (7%)	882 (6%)	4163 (11%)	768 (5%)	5371 (6%)	849 (5%)
Warehouse Worker	9538 (12%)	2239 (15%)	4575 (12%)	1525 (10%)	10913 (13%)	1858 (10%)
Administrative Assistant	4821 (6%)	633 (4%)	1969 (5%)	861 (5%)	4250 (5%)	802 (4%)
Janitor	4388 (5%)	1022 (7%)	2490 (6%)	1148 (7%)	5846 (7%)	1135 (6%)
Certified Nursing Assistant	9093 (11%)	1833 (12%)	3000 (8%)	1626 (10%)	7884 (9%)	1995 (11%)
Server	7914 (10%)	1306 (9%)	3160 (8%)	1443 (9%)	8027 (9%)	2081 (12%)
Receptionist	7160 (9%)	969 (6%)	3328 (9%)	1209 (8%)	7529 (9%)	1574 (9%)
Housekeeper	1929 (2%)	382 (3%)	838 (2%)	307 (2%)	2163 (3%)	719 (4%)
Cook	8606 (10%)	1402 (9%)	3421 (9%)	1580 (10%)	8574 (10%)	2165 (12%)
Landscaper	2671 (3%)	634 (4%)	1513 (4%)	718 (4%)	3747 (4%)	729 (4%)
Panel B: Application Counts per Occupation-CBSA Pair						
Construction Worker	35 (5%)	36 (5%)	36 (5%)	37 (6%)	36 (5%)	35 (5%)
Baker	15 (2%)	15 (2%)	17 (3%)	16 (2%)	16 (2%)	14 (2%)
Assembler	28 (4%)	27 (4%)	28 (4%)	28 (4%)	27 (4%)	28 (4%)
Retail Sales	84 (13%)	82 (12%)	84 (13%)	84 (13%)	83 (12%)	83 (13%)
Cashier	30 (5%)	29 (4%)	31 (5%)	28 (4%)	30 (5%)	29 (4%)
Truck Driver	66 (10%)	65 (10%)	65 (10%)	68 (10%)	66 (10%)	66 (10%)
Warehouse Worker	56 (8%)	55 (8%)	57 (9%)	56 (8%)	56 (8%)	55 (8%)
Administrative Assistant	36 (5%)	36 (5%)	37 (6%)	36 (5%)	36 (5%)	37 (6%)
Janitor	36 (5%)	35 (5%)	38 (6%)	37 (6%)	36 (5%)	35 (5%)
Certified Nursing Assistant	64 (10%)	64 (10%)	62 (9%)	63 (9%)	64 (10%)	64 (10%)
Server	33 (5%)	34 (5%)	32 (5%)	33 (5%)	34 (5%)	34 (5%)
Receptionist	50 (8%)	49 (7%)	51 (8%)	50 (7%)	50 (8%)	49 (7%)
Housekeeper	38 (6%)	38 (6%)	38 (6%)	39 (6%)	38 (6%)	38 (6%)
Cook	58 (9%)	58 (9%)	58 (9%)	58 (9%)	58 (9%)	56 (8%)
Landscaper	35 (5%)	36 (5%)	35 (5%)	35 (5%)	36 (5%)	36 (5%)

Note: Panel A reports estimated new hire counts per occupation, and the proportion of new hires each occupation represents per CBSA is reported in brackets. Hiring counts by NAICS code are sourced from Quarterly Workforce Indicators (U.S. Census Bureau 2023b), and the percent of each NAICS code employed by in each occupation SOC Code is sourced from Occupational Employment and Wage Statistics (U.S. Bureau of Labor Statistics 2025). Estimated new hires per occupation are calculated by multiplying industry-level hires by the occupation's employment share within each NAICS code, then summing across all industries. I match SOC codes to occupations as follows. Code 43-6010 is Administrative Assistant; 51-200 is Assembler; 51-3010 is Baker; 41-2010 is Cashier; 31-1100 is Certified Nursing Assistant; 47-2040, 47-2050, 47-2060, 47-2070, 47-2080, 47-2180 are Construction Worker; 35-2010 is Cook; 37-2012 is Housekeeper; 37-2011 is Janitor; 37-3011 is Landscaper; 43-4170, 43-4080, 43-4050 are Receptionist; 41-2030, 41-2020 are Retail Sales; 35-3030 is Server; 53-3030 and 53-3090 are Truck Driver; 53-7062, 53-7064, 53-7065 are Warehouse Worker. Panel B reports application counts, where the proportion of applications each occupation represents per CBSA is reported in brackets.

Table A20: Observation Weights

Occupation	Seattle, WA	Spokane, WA	Salt Lake City, UT	Provo, UT	Denver, CO	Colorado Springs, CO
Panel A: Weighting Approach 1—weight occupations (across all CBSAs)						
Construction Worker	1.46	1.46	1.46	1.46	1.46	1.46
Baker	0.20	0.20	0.20	0.20	0.20	0.20
Assembler	0.67	0.67	0.67	0.67	0.67	0.67
Retail Sales	0.71	0.71	0.71	0.71	0.71	0.71
Cashier	1.16	1.16	1.16	1.16	1.16	1.16
Truck Driver	0.69	0.69	0.69	0.69	0.69	0.69
Warehouse Worker	1.43	1.43	1.43	1.43	1.43	1.43
Administrative Assistant	0.96	0.96	0.96	0.96	0.96	0.96
Janitor	1.15	1.15	1.15	1.15	1.15	1.15
Certified Nursing Assistant	1.04	1.04	1.04	1.04	1.04	1.04
Server	1.87	1.87	1.87	1.87	1.87	1.87
Receptionist	1.14	1.14	1.14	1.14	1.14	1.14
Housekeeper	0.43	0.43	0.43	0.43	0.43	0.43
Cook	1.16	1.16	1.16	1.16	1.16	1.16
Landscaper	0.73	0.73	0.73	0.73	0.73	0.73
Panel B: Weighting Approach 2—weight occupations (within each CBSA)						
Construction Worker	1.52	1.63	1.78	2.08	1.22	1.09
Baker	0.27	0.16	0.18	0.18	0.16	0.18
Assembler	0.79	0.48	0.78	0.74	0.59	0.36
Retail Sales	0.68	0.70	0.70	0.74	0.74	0.65
Cashier	1.04	1.00	1.11	1.36	1.19	1.46
Truck Driver	0.67	0.60	1.10	0.47	0.64	0.47
Warehouse Worker	1.37	1.80	1.37	1.14	1.54	1.24
Administrative Assistant	1.08	0.78	0.91	1.00	0.93	0.80
Janitor	0.98	1.29	1.12	1.30	1.28	1.19
Certified Nursing Assistant	1.14	1.26	0.83	1.08	0.97	1.15
Server	1.93	1.69	1.69	1.83	1.86	2.25
Receptionist	1.15	0.87	1.12	1.01	1.19	1.18
Housekeeper	0.41	0.44	0.38	0.33	0.45	0.70
Cook	1.20	1.07	1.01	1.14	1.17	1.42
Landscaper	0.61	0.78	0.74	0.86	0.82	0.75

Note: application weights used in robustness checks are reported. Weights are constructed as the ratio of an occupation's (or occupation-by-CBSA's) share of total new hires to its share of total applications (see Table A19). These weights adjusts for over- or under-representation of occupations in the applicant pool relative to their prevalence in actual hiring.