

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

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Abstract

Thousands of randomly generated, fictitious resumes were submitted to job postings in pairs where the treatment resume contained pronouns listed below the name and the control resume did not. Two treatments were considered: nonbinary “they/them” and binary “he/him” or “she/her” pronouns congruent with implied sex. Results show that disclosing nonbinary pronouns reduces positive employer response by 5.4 to 5.5 percentage points; estimates are statistically significant and robust to the Heckman-Siegelman critique. There is suggestive evidence that discrimination is larger (approximately double) in Republican than Democratic geographies, potentially reflecting attitudinal differences. Applicants with multiple minority identities are doubly disadvantaged: for example, disclosing nonbinary pronouns while applying to a male-dominated occupation as a female reduces positive employer response by 10.9 to 11.8 percentage points relative to males who do not disclose pronouns. By comparison, there is limited evidence that disclosing binary pronouns reduces positive employer response.

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

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Sharing pronouns is becoming increasingly common in social interactions and the workplace. This practice has also spread to the job market: job seekers now have the option to include pronouns on resumes, with multiple online articles discussing whether and how to do so (Kohler 2021; Mahtani 2022; Rorris-Crow 2022). However, pronoun disclosure carries additional identity signals and thus potentially opens applicants up to discrimination. This may be especially true when pronoun disclosure reveals a minority gender identity, as for nonbinary applicants. In this study, I investigate hiring discrimination against nonbinary applicants who disclose “they/them” pronouns; in doing so, discrimination against cisgender applicants who disclose binary “he/him” or “she/her” pronouns is also investigated. By comparing discrimination faced by nonbinary and cisgender applicants who disclose pronouns, discrimination against applicants who disclose “they/them” pronouns can be decomposed into the portion driven by the act of pronoun disclosure generally and by the applicant’s nonbinary gender identity. A resume audit study design is leveraged, with pronoun disclosure as the treatment of interest.

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

Inspired by Bertrand and Mullainathan (2004), correspondence studies have become a common experimental method used to causally estimate discrimination. Beginning with

race, these field experiments have been used to investigate discrimination against a host of marginalized groups in multiple contexts (Baert 2018 provides a review). Most relevant to this study are correspondence studies focused on hiring discrimination against the LGBT community, and gender-diverse populations in particular. Granberg et al. (2020) used an unmatched correspondence study to investigate hiring discrimination against transgender men and women in Sweden. They found that transgender applicants are 6 percentage points less likely to receive a positive employer response than cisgender applicants; estimates are only robust to the Heckman-Siegelman critique when comparing transgender applicants to the dominant gender in male- or female-dominated occupations.¹ Considering nonbinary people, Business.com conducted a non-academic unmatched correspondence study evaluating hiring discrimination against nonbinary applicants (McGonagill 2023). In this study, two identical resumes were generated for the same fictitious applicant, where the only difference is that one has “they/them” pronouns listed below the gender-ambiguous name and the other does not. In total, applications were sent to 180 remote, entry-level business positions requiring an undergraduate degree. McGonagill found that the control applicant received 9 percent more interest from employers.

This study contributes to existing research as the first large-scale study investigating hiring discrimination against applicants who disclose pronouns. From May to October 2023, 3,985 matched pairs of resumes were sent in response to job postings in 15 occupations across six U.S. cities. As in McGonagill (2023), the characteristic of interest in this study is pronouns listed below the name. The large-scale nature of this experiment alongside the fact that resumes are randomly generated (versus identical except for treatment assignment) and multiple occupations are explored increases external validity, power, and precision; reduces template bias; and enables the exploration of additional hypotheses. Further, unlike in McGonagill (2023), this study leverages two distinct treatments: nonbinary pronouns (“they/them,” signaling the applicant is nonbinary and disclosing pronouns) and binary pronouns congruent with sex implied by name (“he/him” or “she/her,” signaling the applicant is cisgender and disclosing pronouns).

The inclusion of two treatments is a key contribution of this paper. First, it enables the decomposition of discrimination faced by applicants who disclose “they/them” pronouns into the portion driven by applicants’ nonbinary gender identity and by the act of pronoun disclosure (which cisgender applicants who disclose pronouns also face). This is important because, in recent years, pronoun disclosure has become divisive. Sentiment is split along

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

political lines: a 2022 YouGov poll found that, when asked to think about information people put on social media profiles, email signatures, or when introducing themselves 40% of Republicans but only 10% of Democrats believe that “people should generally not say / display their pronouns unless asked” (Ballard 2022). As a result, pronoun disclosure carries political and other signals that are communicated regardless of implied gender identity. This is especially pertinent since there is evidence that minority political signals can induce hiring discrimination (Gift and Gift (2015)). Second, it enables the estimation of discrimination faced by cisgender applicants who disclose pronouns.

Following its pre-analysis plan, this study attempts to answer two primary research questions. Do applicants who disclose nonbinary “they/them” pronouns during the hiring process experience discrimination? If so, to what extent can this be explained by identity-based discrimination specific to nonbinary applicants versus the act of pronoun disclosure? This can be achieved by comparing positive employer response rates for applicants disclosing nonbinary pronouns compared to applicants disclosing binary pronouns congruent with implied sex. Secondary hypotheses, informed by existing research and described below, are also explored. These hypotheses consider whether discrimination magnitude varies based on applicant, geographic, occupation, and job posting characteristics.

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

I also investigate whether discrimination differs between nonbinary applicants with male-sounding names and those with female-sounding names. This is motivated by evidence that, within the LGBT community, people assigned male at birth tend to experience worse labor market outcomes than those assigned female. Among homosexuals, international research

consistently shows that while gay men experience a wage gap compared to similar heterosexual peers, lesbian women experience a wage premium (Black et al. 2003; Antecol et al. 2008; Drydakis 2012; Nauze 2015; Waite et al. 2019; Drydakis 2021; Jepsen and Jepsen 2022). In a meta-analysis of hiring discrimination against gay men and lesbian women, Flage (2019) shows that there is consistent evidence of discrimination against both groups, but discrimination is larger on average against gay men. Considering transgender people, longitudinal studies have shown that transgender women’s earnings significantly decrease post-transition while the earnings of transgender men remain unchanged or slightly increase (Schilt and Wiswall 2008; Geijtenbeek and Plug 2018).

To distinguish between statistical and taste-based discrimination, I consider whether discrimination decreases as relevant experience increases. If additional information about an applicant’s ability to successfully work in an occupation reduces discrimination, this indicates the presence of statistical discrimination. Following Becker (1957), I also consider whether employers may be discriminating on behalf of their customers by comparing occupations with higher and lower levels of customer interaction. If discrimination is higher in occupations requiring more customer interaction, this suggests employers may be discriminating based on customer taste. Finally, I consider whether discrimination is heightened in male- or female-dominated occupations. This is motivated by Granberg et al. (2020), who found robust evidence of discrimination against transgender men and women in male-dominated and female-dominated occupations only.

I find that for the average applicant, disclosing “they/them” pronouns reduces positive employer response by an estimated 5.4 to 5.5 percentage points compared to no pronoun disclosure. Compared to applicants who disclose binary “he/him” or “she/her” pronouns, positive employer response is reduced by 3.6 to 3.8 percentage points. Hence, an estimated 67% to 70% of discrimination against applicants disclosing “they/them” pronouns is due to nonbinary gender identity. However, since the difference in positive employer response between applicants who disclose binary pronouns and no pronouns has limited statistical significance, gender identity may be driving up to 100% of discrimination. Finally, there is suggestive evidence that discrimination is higher in Republican geographies and that applicants with multiple minority identities are doubly disadvantaged.

This paper is structured as follows. In Section 1, I describe the audit study design: how resumes are constructed, geography and occupation selection, and the process used to collect data. In Section 2, empirical strategy (as outlined in the pre-analysis plan) is described. In Section 3, I present empirical results: summary statistics and regression estimates. In Section 3.5, I use the Neumark (2012) method to address the Heckman-Siegelman critique. In Section 4, I provide context by comparing discrimination estimates associated with pronoun

disclosure against estimates found for other discriminated groups: females in male-dominated occupations, and males in female-dominated or non-dominated occupations. Finally, Section 5 concludes.

1 Audit Study Design

1.1 Resume Construction

1.1.1 Randomization Process

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

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

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

- Pronouns (Section 1.1.2): resumes are assigned one of nonbinary “they/them” pronouns, binary “he/him” or “she/her” pronouns congruent with implied sex, or no pronouns. Because I am most interested in identifying discrimination against applicants who disclose “they/them” pronouns, conditional on disclosure resumes have a

two-thirds chance of being assigned nonbinary and one-third chance binary pronouns. Pronouns are matched different: exactly one resume in each pair has no pronouns.

- Summary (Section 1.1.3): resumes are assigned a summary, selected without replacement from a list of 12 inputs, where four are summaries and eight have no summary. Resumes are matched different: no two resumes will have the same summary (however, both resumes can have no summary and one resume can have a summary while the other does not).
- Education Level (Section 1.1.4): resumes are assigned an education level where probabilities are occupation-specific and informed by observed prevalence. Resumes are matched same in terms of the highest level of education received: conditional on having a high school diploma, applicants' high schools are nearby and have similar test scores. Resumes are matched different in terms of high school name and post-secondary concentration (if applicable).
- Work Experience, 2015-2017 (Section 1.1.5): in the last two years of high school, applicants were assigned one of two work experiences (or no work experience). Experience is selected without replacement from a list of seven inputs, where five are no experience. Resumes are matched different: no two applicants can have the same work experience (though they can both have no work experience during this period).
- Work Experience, 2017-present (Section 1.1.5): after high school, applicants are assigned four work experiences. Experiences are selected without replacement from 43 possible position and description pairs. Resumes are matched same in terms of whether the applicant's last job is in the job posting occupation and years of experience in the job posting occupation. Resumes are matched different in terms of job titles, company names, and position descriptions.
- Skills Listed: each applicant has six skills listed. Skills are randomly selected without replacement from a list of 18 skills; three are selected from a nine occupation-specific skills, the others are selected from a nine skills that are independent of occupation. Resumes are matched different: applicants will never have the same skill listed.

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

1.1.2 Pronoun Treatments

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

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

1.1.3 Summary

A “summary” is a brief, typically one-sentence objective or summary statement that may be included at the top of a resume. An example of a summary input for applicants applying as an administrative assistant is “To secure a position with a well-established organization with a stable environment that will lead to a lasting relationship.” Summaries are occupation-

specific, and each occupation randomizes across four summary inputs (or no summary).

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 job descriptions were taken. Idaho was chosen specifically because it is adjacent to all three states of interest (Washington, Utah, and Colorado). Ordering resumes by date of upload to the job board website, summary inputs were taken from the first four resumes which included a summary or objective statement. In some cases, summaries were deemed inappropriate and disregarded (e.g., if the applicant discussed their intention to make a career change or where the summary could not be made generalizable across resumes that would be randomized) or adjusted (to ensure generalizability).

1.1.4 Education

For each occupation, the percentage of applicants whose highest education level is GED, high school diploma, Associate’s degree, and Bachelor’s degree was identified by averaging resume data available on the large job board across the six geographies in this study. These percentages determine the occupation-specific probability of resume pairs being randomly assigned each education level. Applicants with a high school diploma received that degree in 2017; applicants with a GED received that degree in 2019. Applicants with an Associate’s degree achieved that degree between 2019 and 2022; applicants with a Bachelor’s degree achieved that 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.² In total, 2,510 observations

²In cases where there did not exist 20 resumes of people currently holding that occupation in the geog-

were collected, where each observation includes the school name and concentration. From this data, the most common four degree concentrations were identified for applicants with Associate’s and Bachelor’s degrees held by workers in each occupation. In addition, the two most common schools these degrees come from (for each of the six geographies) were identified. Concentrations and schools are then used as occupation and geography-specific education inputs.

1.1.5 Work Experience

One challenge of randomizing work experience in the context of this study is that applicants are applying in various cities in relatively low-skill occupations. Given that low-skill workers tend to have lower geographic mobility (Schmutz et al. 2021), the experiment is designed such that fictitious applicants are all local to the city they are applying within. This must be reflected in their work experience; hence, company names must be geography-specific. Because applicants are “matched different” in terms of the companies they work at, sourcing entire work experience sections from actual resumes becomes infeasible: this may require finding a very large number of a particular type of company (e.g., construction companies) in each city. Finding so many company names, ensuring alignment between company names and job descriptions, and verifying the existence of the company during the claimed period of employment make this approach prohibitively difficult.

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

To identify the occupation-specific set of 33 work experience inputs outside of the occupation of interest, data was scraped from resumes of job seekers on the large job board

raphy of interest with one of these degrees, all available data was scraped

website. For each geography and occupation, resume data was scraped from 150 resumes of applicants currently holding that occupation³. In total, 11,705 observations were collected, where each observation includes the last three positions listed on the resume. Using this data, for each occupation the most common 12 positions held by workers before getting a job in the occupation of interest were identified. These 12 positions make up the total set of 33 inputs, where their relative frequency is designed to be representative (reflecting how likely it is that someone in the occupation of interest previously held another position). Pooling the 43 work experience options across all 15 occupations, and re-using positions and job descriptions where possible, generates the total set of 188 work experience options.

For each of the 188 work experience options, job descriptions were taken from actual resumes for workers living in Idaho who currently hold that position.⁴ Ordering resumes by date of upload to the job board website, job descriptions were taken from the first resumes which included job descriptions listed in point form (or that could be easily converted into point form). As much as possible, descriptions were kept as-is (e.g., typos and grammatical errors were retained), but were adjusted or skipped as needed (e.g., if descriptions were too specific to the company of employment). While job descriptions were not city-specific, company names were. They were sourced from the list of most common companies worked at by job seekers who currently hold a position in that occupation and city. For some occupations, additional companies were found as needed. Companies were carefully selected to align with the job descriptions. For example, for a construction worker job description mentioning excavation, a company that appeared to offer excavation services was chosen. Similarly, for a receptionist role involving dental records, a company providing dental services was selected.

1.1.6 Names

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

³In cases where there did not exist 150 resumes of people currently holding that occupation in the geography of interest, all available data was scraped

⁴A 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 job descriptions were taken. Idaho was chosen specifically because it is adjacent to all three states of interest (Washington, Utah, and Colorado).

The last names used in this study are provided in Table 2. These names were randomly selected from a list of 59 last names which met two criteria. First, they are in the top 100 most common last names in the United States from U.S. Census Bureau (2021b). Second, the percentage of the population with the last name that are white is less than 80 and the percent 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 2021b). 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 3. Note that 10 U.S. phone numbers were obtained for this study—two for each local area code (206 in Seattle, WA; 509 in Spokane, WA; 720 in Denver, CO; 719 in Colorado Springs, CO; and 801 in Salt Lake City, UT and Provo, UT).

1.1.7 Resume Formatting

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

1.2 Geography Selection

Census Bureau Statistical Areas (CBSAs) chosen as geographies of interest within which to distribute fictitious resumes are provided in Table 4. Geographies were selected to include pairs of CBSAs that met three criteria. First, to impose consistency in discrimination legislation across states, CBSAs are in states which have legislation prohibiting labor market discrimination on the basis of both gender identity and sexual orientation. Second, to ensure there would be a sufficient number of job postings in all geographies, all CBSAs have a population of at least 500 thousand. Finally, CBSA pairs must be in the same state and one must be categorized as Democratic and the other Republican. Note also that two of the three pairs are near each other: CBSA pairs in Utah and Colorado are neighboring. In all,

this design prioritizes consistency in macroeconomic environments as well as state policy and legislation, to focus on attitudinal differences between Democratic and Republican regions.

An implication of focusing on states which have legislation prohibiting labor market discrimination on the basis of gender identity and sexual orientation is that hiring discrimination against nonbinary applicants in these states may be lower on average than in states which 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 which select into them may be less discriminatory against these groups on average.

1.3 Occupation Selection

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

The 15 occupations included in this study are in general lower skill, requiring no more than a high school education. This influences external validity and was done for a few reasons. First, this study seeks to compare discrimination across occupations which vary in worker composition and degree of customer interaction. This requires applying across a multitude of occupations which is less feasible in higher-skill occupations where there are more barriers to application (e.g., specialized job boards and more communication among employers). Second, this study seeks to compare discrimination across geographies which vary politically; for each occupation, there must be sufficient job postings in all geographies. Again, this is less feasible with higher-skill occupations which tend to be more geographically

concentrated (e.g., there are limited computer programming job postings in Spokane). Third, the majority of U.S. workers do not have post-secondary education: 62.1% have below a Bachelor’s degree and 51.6% have below an Associate’s degree (U.S. Census Bureau 2022a). Understanding discrimination in the context of these occupations is thus important.

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

1.4 Data Collection Process

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

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

enabled RAs to check the company name against a list of hundreds of job agencies; if the job was posted by a job agency, the job posting was rendered ineligible. Job agencies typically respond positively to all applicants since they seek to match a wide range of applicants with employers (regardless of skill or background experience)—hence, these “employers” make poor experimental targets.

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

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

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

2 Empirical Strategy

The empirical strategy employed here closely follows a pre-analysis plan registered with the American Economic Association prior to data collection (Eames 2023). A set of pre-defined regressions are run to investigate primary and secondary hypotheses. Through this paper, the following notation is used when discussing logistic regression:

$$P(y_{ij} = 1) = \frac{1}{1 + e^{-z}}$$

where y_{ij} is an indicator variable which equals 1 if applicant i received a positive response from firm j and z is the model (to be described below). For all regressions, standard errors are clustered at the job posting level. In the pre-analysis plan, standard errors were said to be clustered at the “firm” level; since the experimental design allows for multiple applications to the same firm (e.g., if they are located in different states; see Section 1.4 for more information on job posting eligibility) this has been modified for clarity.

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

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

where α_j are job posting fixed effects, NB_i is an indicator variable which equals 1 if the resume has nonbinary “they/them” pronouns listed, B_i is an indicator variable which equals 1 if the resume has binary “he/him” or “she/her” pronouns listed, X_i is a vector of resume characteristics that may influence baseline employer response, Z_j is a vector of firm and job posting characteristics which many influence baseline employer response, and ε_{ij} is an error term. Multiple specifications are run, where some include and some exclude (α_j, X_i, Z_j) ; when “excluding” α_j it is replaced with intercept α . Estimates $\hat{\gamma}, \hat{\lambda}$ can be interpreted as discrimination against applicants who disclose pronouns. Note that similar to standard errors, in the pre-analysis plan α_j was said to be “firm” fixed effects; this has been similarly modified for clarity.

To determine the extent to which discrimination against applicants who disclose “they/them” pronouns is rooted in gender identity, the following logistic regression is run excluding control observations (i.e., all resumes list pronouns):

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

Similar to equation (1), multiple specifications are run. Defining ξ as the proportion of discrimination faced by applicants who disclose “they/them” pronouns attributable to their nonbinary gender identity, this can be estimated:

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

The remaining discrimination can be attributed to the act of pronoun disclosure (independent of which pronouns are disclosed).

For each secondary hypothesis, (1) is run separately for each group being compared. In addition, the following logistic regressions are run where each tests a different hypothesis:

$$(4.1) \quad z = \alpha_j + \gamma_1 NB_i + \gamma_2[NB_i \cdot R_j] + \lambda_1 B_i + \lambda_2[B_i \cdot R_j] + X'_i \beta_1 + Z'_j \beta_2 + \varepsilon_{ij}$$

$$(4.2) \quad z = \alpha_j + \gamma_1 NB_i + \gamma_2[NB_i \cdot RLE_i] + \lambda_1 B_i + \lambda_2[B_i \cdot RLE_i] + X'_i \beta_1 + Z'_j \beta_2 + \varepsilon_{ij}$$

$$(4.3) \quad z = \alpha_j + \gamma_1 NB_i + \gamma_2[NB_i \cdot M_i] + \lambda_1 B_i + \lambda_2[B_i \cdot M_i] + X'_i \beta_1 + Z'_j \beta_2 + \varepsilon_{ij}$$

$$(4.4) \quad z = \alpha_j + \gamma_1 NB_i + \gamma_2[NB_i \cdot MD_j] + \gamma_3[NB_i \cdot FD_j] + \lambda_1 B_i + \lambda_2[B_i \cdot MD_j] + \lambda_3[B_i \cdot FD_j] + X'_i \beta_1 + Z'_j \beta_2 + \varepsilon_{ij}$$

$$(4.5) \quad z = \alpha_j + \gamma_1 NB_i + \gamma_2[NB_i \cdot HC_j] + \gamma_3[NB_i \cdot LC_j] + \lambda_1 B_i + \lambda_2[B_i \cdot HC_j] + \lambda_3[B_i \cdot LC_j] + X'_i \beta_1 + Z'_j \beta_2 + \varepsilon_{ij}$$

$$(4.6) \quad z = \alpha_j + \gamma_1 NB_i + \gamma_2[NB_i \cdot EO_j] + \gamma_3[NB_i \cdot GS_j] + \gamma_4[NB_i \cdot SB_j] + \lambda_1 B_i + \lambda_2[B_i \cdot EO_j] + \lambda_3[B_i \cdot GS_j] + \lambda_4[B_i \cdot SB_j] + X'_i \beta_1 + Z'_j \beta_2 + \varepsilon_{ij}$$

Interaction variables (R_j, HC_j, LC_j , etc.) are described in Table 8. Versions of equations (4.1), (4.4), (4.5) are investigated which replace indicator variables with continuous variables: Republican vote share, the share of males in the workforce, and O*NET customer interaction score respectively. These continuous interaction variables are described in Table 9. Similar to equation (1), multiple specifications are run.

A final regression is run including all interactions simultaneously:

$$(5) \quad z = \alpha_j + \gamma_1 NB_i + \gamma_2[NB_i \cdot R_j] + \gamma_3[NB_i \cdot M_i] + \gamma_4[NB_i \cdot RLE_i] + \gamma_5[NB_i \cdot MD_j] + \gamma_6[NB_i \cdot FD_j] + \gamma_7[NB_i \cdot HC_j] + \gamma_8[NB_i \cdot LC_j] + \gamma_9[NB_i \cdot EO_j] + \gamma_{11}[NB_i \cdot SB_j] + \lambda_1 B_i + \lambda_2[B_i \cdot R_j] + \lambda_3[B_i \cdot M_i] + \lambda_4[B_i \cdot RLE_i] + \lambda_5[B_i \cdot MD_j] + \lambda_6[B_i \cdot FD_j] + \lambda_7[B_i \cdot HC_j] + \lambda_8[B_i \cdot LC_j] + \lambda_9[B_i \cdot EO_j] + \lambda_{10}[B_i \cdot GS_j] + \lambda_{11}[B_i \cdot SB_j] + \varepsilon_{ij}$$

As with equation (1), multiple specifications are run. As with equations (4.1), (4.4), (4.5) a second version is run which replaces indicator variables with continuous variables.

Resume characteristics in vector X_i are described in Table 10; job posting and firm characteristics in vector Z_j are described in Table 11.

3 Results

Results presented in this section define positive employer response per the study's pre-analysis plan.⁵ Results associated with the alternative definition are presented in Appendix B.⁶ Results are consistent across definitions overall, but there is stronger evidence of discrimination against applicants disclosing binary pronouns with the latter definition.

⁵“Employer response [is] viewed as ‘positive’ if they contact the applicant and either offer an interview or request the applicant contact them” (Eames 2023).

⁶Any response that could be interpreted positively is viewed as positive.

3.1 Summary Statistics

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

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

3.2 Primary Hypotheses

Panel A of Table 15 reports regression results for equation (1). Note that the interpretation of regression coefficients in specification (E) is unique: when including job posting fixed effects, resume pairs with concordant employer responses are excluded from analysis, and only pairs with discordant employer responses are retained. Hence, marginal effects reported in (E) are conditional on discordant employer responses. As a result, I focus on coefficient estimates from (A) to (D) and include (E) as an additional check that results are consistent in terms of sign and statistical significance. Panel A shows that, for the average applicant, disclosing nonbinary “they/them” pronouns reduces the rate of positive employer response by 5.4 to 5.5 percentage points relative to no pronoun disclosure; this estimate is statistically significant at the 1% level and robust to all specifications. Disclosing binary “he/him” or “she/her” pronouns congruent with name-implied sex reduces the rate of positive employer response by 1.7 to 1.8 percentage points relative to no pronoun disclosure. While these estimates are statistically insignificant except for specification (E), using the alternative definition of positive employer response yields slightly higher estimates (2.0 to 2.2 percentage points) that are statistically significant at the 10% level in all specifications except (E); this can be seen in Table 16. There is thus strong evidence of discrimination against applicants who disclose

nonbinary “they/them” pronouns and limited evidence of discrimination against applicants who disclose binary “he/him” or “she/her” pronouns congruent with implied sex (though power is limited for this group due to lower sample size).

Panel B of Table 15 reports regression results for equation (2), and shows that there is a statistically significant difference in discrimination between applicants who disclose nonbinary “they/them” pronouns and applicants who disclose binary “he/him” or “she/her” pronouns congruent with name-implied sex. Nonbinary pronoun disclosure reduces the rate of positive employer response by 3.6 to 3.8 percentage points compared to binary pronoun disclosure; this estimate is statistically significant at the 5% level and robust to all specifications. Combining Panels A and B, from equation (3) it can be estimated that 66% to 70% of discrimination faced by applicants who disclose “they/them” pronouns is gender identity-based; the remainder may be driven by the act of pronoun disclosure. However, given the limited statistical significance of discrimination against those who disclose binary pronouns, gender identity may be responsible for as much as 100% of observed discrimination.

3.3 Secondary Hypotheses: Differences by Geographic Politics

Panel C of Table 17 reports the results of equation (4.1); it carries two implications. First, there is suggestive evidence that discrimination against applicants disclosing nonbinary “they/them” pronouns is larger in Republican than in Democratic geographies. For the average applicant, disclosing these pronouns is estimated to reduce positive employer response rates by between 3.5 to 3.6 percentage points at baseline. In Republican areas, positive employer response is estimated to be reduced by an additional 3.7 to 4.0 percentage points (i.e., discrimination more than doubles). In four of five specifications, this increase is statistically significant at the 5% level. This may be driven by attitudinal differences between Republican and Democratic areas: city pairs are located in the same state to control for state-level macroeconomic environments, policy, and legislation. In addition, two of the three city pairs are neighboring, increasing their environmental similarities.

Second, although discrimination against applicants disclosing binary “he/him” or “she/her” is not statistically different in Republican than Democratic areas, estimates are larger in the former. This is consistent with Gift and Gift (2015), who find that applicants with a minority political affiliation (e.g., signaled liberal through pronoun disclosure in a conservative area) are less likely to receive a positive employer response.

Table 18 reports results associated with Panel C of Table 17, where the geography indicator variable is replaced with a Republican vote share variable. Two specifications are considered, where one includes and one excludes a squared term. In general, coefficient

estimates of the interaction between “they/them” pronoun disclosure and Republican vote share are statistically significant at the 10% level when squared terms are omitted and the 5% level when squared terms are included. This strengthens the case that there is a relationship between political affiliation and discrimination against nonbinary applicants.

3.4 Secondary Hypotheses: All Others

Results of equation (5), which includes all interactions investigated in this study, are reported in Table 19. Results show that there is no evidence that discrimination meaningfully differs between applicants who are implied male and female; with more or less relevant experience; or between occupations with different male-female worker compositions. Further there is limited evidence that there are differences in discrimination based on the extent to which the occupation involves customer interaction. Results do not suggest that employers are discriminating on behalf of their customers: discrimination is highest among low customer-facing occupations.

For applicants disclosing nonbinary “they/them” pronouns, there is no evidence that discrimination meaningfully differs between job postings that include or omit key words and phrases. However, for applicants disclosing binary “he/him” or “she/her” pronouns congruent with name-implied sex, there is some evidence that discrimination is larger when applying to job postings that mention the employer is “equal opportunity” and smaller (even positive) when applying to job postings that mention the employer is a small business. Given limited statistical significance (results are generally significant at the 10% level), this may be noise in the data. In addition, this outcome is not wholly unsurprising when it comes to job postings that mention “equal opportunity:” it is consistent with Bertrand and Mullainathan (2004) who find that discrimination is no lower when employers explicitly state that they are “Equal Opportunity Employers.”

Results of equation (1) when isolating observations within groups, equations (4.2) to (4.6) with indicator and continuous variables, and of equation (5) with continuous variables are reported in Appendix A. Results are consistent with those presented in Tables 15 and 19.

3.5 Robustness Check: Heckman-Siegelman Critique

Heckman and Siegelman (1993) and Heckman (1998) show that if the variance of unobservable determinants of productivity differs between treatment and control groups, correspondence studies can find spurious estimates of discrimination. 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 (2012) 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. Under this assumption (with testable implications), discrimination estimates can be disaggregated into a level part that includes taste-based and first-moment statistical discrimination, and a variance part that includes second-moment statistical discrimination. This adjustment can meaningfully change results: when re-assessing evidence from six resume studies that find evidence of labor market discrimination with sufficient information to correct for this bias, Neumark and Rich (2019) find that unbiased (level) estimates for half of them decrease to near zero, become statistically insignificant, or change sign.

I use this method (via heteroskedastic logistic regression) and results are presented in Table 20; I referenced code provided by Neumark et al. (2016) when generating. Using this method, the unbiased discrimination estimate against applicants who disclose “they/them” pronouns is 5.3 percentage points and statistically significant at the 5% level; there is no evidence that the identifying assumption is violated. Estimated discrimination against applicants who disclose “he/him” or “she/her” pronouns remains statistically insignificant.

4 Magnitude Comparison: Sex Discrimination

Note: the analysis discussed in this section is not included in the study’s pre-analysis plan.

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

Using the same notation detailed in Section 2, I run the following logistic regression:

$$(6) \quad z = \alpha + \gamma NB_i + \lambda B_i + \eta_1 M_i + \eta_2 [M_i \cdot FD_j] + \eta_2 [F_i \cdot MD_j] + X'_i \beta_1 + Z'_j \beta_2 + \varepsilon_{ij}$$

where F_i is an indicator variable that equals 1 if the applicant is implied female.

Regression results are presented in Table 21, and show that applicants who are implied male (through name) experience discrimination in female-dominated and non-dominated occupations: positive employer response rates are 3.5 of 4.8 percentage points lower for

males compared to females in these occupations. Applicants who are implied to be female experience discrimination in male-dominated occupations: positive employer response rates are 5.6 to 6.4 percentage points lower for females compared to males in these occupations. Hence, discrimination against applicants disclosing nonbinary “they/them” pronouns is of a similar magnitude to discrimination faced by males applying in female-dominated and non-dominated occupations and females applying in male-dominated occupations.

Further, there is evidence that discrimination is intersectional: implied female applicants who apply in male-dominated occupations and disclose “they/them” pronouns face positive employer response rates that are 10.9 to 11.8 percentage points lower. Implied male applicants who disclose pronouns and apply in non-dominated or female-dominated occupations are also doubly disadvantaged. This can be seen visually in Figure 4.

5 Discussion

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

Overall, there is strong evidence of discrimination against applicants who disclose nonbinary “they/them” pronouns: doing so was found to reduce positive employer response by 5.4 to 5.5 percentage points. These estimates are statistically significant at the 1% level and robust to the Heckman-Siegelman critique. Further, comparing applicants who disclose “they/them” pronouns to those who disclose “he/him” or “she/her” pronouns congruent with name-implied sex, the former experience a 3.6 to 3.8 percentage point reduction in positive employer response. Hence, for applicants disclosing “they/them” pronouns, an estimated 66% to 70% of discrimination is found to be rooted in their nonbinary gender identity rather than the act of pronoun disclosure more generally. Discrimination estimates may be low relative to the U.S. average since all states in this study have state-level legislation prohibiting labor market discrimination on the basis of gender identity and sexual orientation, true for a minority of states (Movement Advancement Project 2023). While these laws may not themselves protect applicants against discrimination, states which select into them may

be less discriminatory towards people with diverse gender identities on average. Further, while external validity is strong across similar lower-skill occupations, results likely are not generalizable across higher-skill occupations which may have different diversity and equity goals, hiring practices, and hiring managers.

There is limited evidence of discrimination against applicants who disclose binary “he/him” or “she/her” pronouns. Point estimates from the main analysis show that applicants who disclose these pronouns received reduced positive employer response by 1.7 to 1.8 percentage points—however, estimates are statistically insignificant in general. Discrimination estimates using the alternative definition are larger (2.0 to 2.2 percentage points) and in general statistically significant at the 10% level. Whether discrimination exists against this group (and to what magnitude) thus remains in question: limited evidence was found in this study. As such, for applicants disclosing “they/them” pronouns, up to 100% of discrimination may be rooted in their nonbinary gender identity.

Considering how discrimination varies geographically, I find suggestive evidence that discrimination against applicants who disclose “they/them” pronouns is larger in Republican than Democratic geographies. These findings build on research by Tilcsik (2011) who finds that estimates of discrimination against openly gay men in the U.S. vary across states based on differences in political sentiment, policy and legislation, or both. This study controls for state-level economic environments, policy, and legislation by including pairs of Republican and Democratic geographies located in the same state. As such, differences in geographic politics are focused on ideology and attitudes. Though not statistically different, for applicants who disclose binary “he/him” or “she/her” pronouns discrimination point estimates are larger in Republican geographies. Since disclosing pronouns can be interpreted as a political signal, this is consistent with Gift and Gift (2015) who find evidence of discrimination against applicants who signal a minority political affiliation. It is important to underscore that these findings are suggestive and not causal: it may also be that geographic politics are correlated with other factors that are leading to differences in discrimination.

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

Considering how discrimination varies across applicant and occupation characteristics yields generally null results. There is no evidence that discrimination against either pronoun

disclosure group meaningfully differs based on implied sex. This is in contrast to other LGBT groups, where those assigned male at birth typically experience worse labor market outcomes and higher rates of discrimination. There is similarly no evidence that discrimination differs based on the applicant’s years of relevant experience, and thus no evidence of statistical discrimination. Finally, there is no evidence that discrimination differs based on occupation worker composition (i.e., across male-dominated, non-dominated, and female-dominated occupations). This differs from the findings of Granberg et al. (2020) who document evidence of discrimination against transgender men and women only in male- and female-dominated occupations and not in mixed occupations. Comparing discrimination across occupations with different levels of customer interaction shows no evidence that employers are discriminating on behalf of their customers: discrimination is highest among low customer-facing occupations.

Additional questions remain, especially when it comes to higher-skill occupations, the specific relationship between Republican vote share and discrimination magnitude, and discrimination intersectionality for people with multiple minority identities. When it comes to applicants disclosing binary “he/him” or “she/her” pronouns congruent with name-implied sex, discrimination estimates are low and evidence is weaker in general. Additional work focused on more precise estimates of discrimination against this group is warranted, especially if the practice of pronoun disclosure in the workplace continues to grow in popularity among cisgender workers.

Tables and Figures

Table 1: First Names Used in Study

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

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

Table 2: Last Names Used in Study

Last Name	Name Popularity		Racial Composition		
	Rank	Count (1,000s)	% White	% African American	% Hispanic
Anderson	15	784	75.2	18.9	2.1
Thomas	16	756	52.6	38.8	2.6
Lewis	29	532	58.2	34.8	2.6
Allen	33	483	67.6	26.2	2.4
Nelson	43	425	77.7	16.0	2.0
Campbell	47	386	73.7	20.5	2.1
Phillips	52	361	76.7	17.1	2.2
Collins	59	330	71.6	22.4	2.2
Morris	62	319	73.6	20.1	2.2
Reed	73	277	71.3	22.6	2.3
Watson	81	253	66.0	27.9	2.3
James	85	249	51.6	38.9	2.6

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

Table 3: Full Names Used in Study

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

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

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 1: Resume Format 1 Example

Adrian Nelson

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Work Experience

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

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

July 2020 - August 2021 Target, Cashier

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

April 2019 - June 2020 Wendy's, Crew Member

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

August 2017 - March 2019 Outback Steakhouse, Host

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

Education

2017 Addenbrooke Classical Academy: High School Diploma

Skills

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

Certifications: CNA, CPR

Figure 2: Resume Format 2 Example

Table 4: Geographies Used in this Study

CBSA	Population		2020 Presidential Votes	
	Count (1,000s)	Density	% Republican	Category
Seattle-Tacoma-Bellevue, WA	3,980	678	30	Democratic
Spokane-Spokane Valley, WA	582	103	52	Republican
Salt Lake City, UT	1,233	160	43	Democratic
Provo-Orem, UT	648	120	68	Republican
Denver-Aurora-Lakewood, CO	2,967	356	46	Democratic
Colorado Springs, CO	746	278	54	Republican

Note: CBSA population data is sourced from the U.S. Census Bureau (2021a), land square footage from TIGERweb U.S. Census Bureau (2020), and 2020 Presidential voting records from MIT Election Data and Science Lab (2018).

Table 5: Occupations Used in this Study

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

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

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

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

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

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

Table 8: Interaction Variables

Notation	Variable	Description
R_j	Republican Geography	Equals 1 if the job is located in a Republican geography (Spokane, WA; Provo, UT; Colorado Springs, CO)
M_i	Implied Male	Equals 1 if the applicant is implied to be male (through name assignment)
RLE_i	Relevant Experience	Equals the years of “relevant” experience the applicant has. Note that work experience is defined as “relevant” if it is in the position being applied for (e.g., if an applicant is applying to a janitor position, years of janitorial experience)
MD_j	Male-Dominated	Equals 1 if the applicant is applying in a male-dominated occupation (construction worker, truck driver, warehouse worker, janitor, landscaper)
FD_j	Female-Dominated	Equals 1 if the applicant is applying in a female-dominated occupation (receptionist, cashier, housekeeper, certified nursing assistant, administrative assistant)
HC_j	High Customer-Facing	Equals 1 if the applicant is applying in a high customer interaction occupation (receptionist, cashier, retail salesperson, server)
LC_j	Low Customer-Facing	Equals 1 if the applicant is applying in a low customer interaction occupation (certified nursing assistant, administrative assistant, baker, assembler / fabricator, warehouse worker, janitor, landscaper)
EO_j	Equal Opportunity	Equals 1 if the job posting includes the text “EOE,” “EEO,” “Equal Opportunit,” “Equal-Opportunit,” “Equal Employment,” or “Equal-Employment”
GS_j	Gender or Sexuality	Equals 1 if the job posting includes the text “gender” or “sexual”
GS_j	Small Business	Equals 1 if the job posting includes the text “small bus,” “small-bus,” “small com,” “small-com,” “small firm,” “smal-firm,” “small empl,” “small-empl,” “local bus,” “local-bus,” “locally own,” “locally-own,” “locally op,” “locally-op,” “family bus,” “family-bus,” “family own,” “family-own,” “small, independent bus,” “small independent bus,” “small team,” “small but growing,” or “small and busy”

Table 9: Interaction Variables (Continuous Versions)

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

Table 10: Resume Characteristics (X_i Control Variables)

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

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

Table 11: Firm and Job Characteristics (Z_j Control Variables)

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

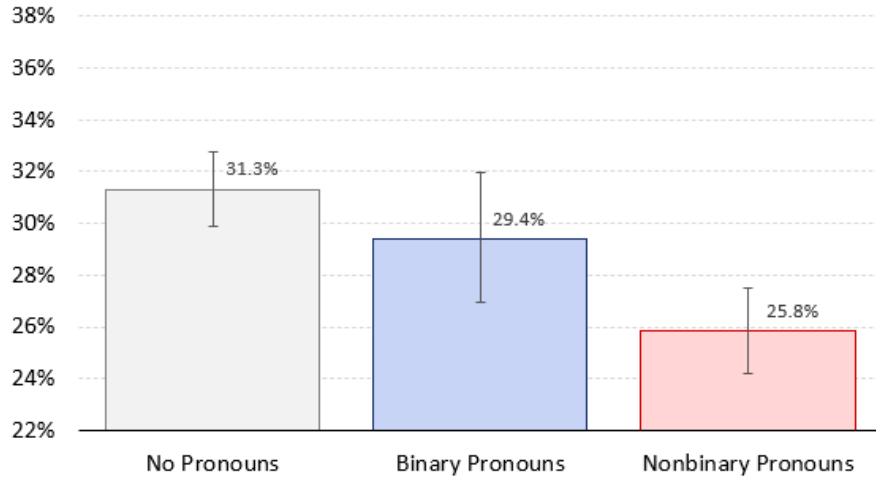


Figure 3: Positive Employer Response: Pronoun Disclosure

Table 12: Differences in Positive Employer Response by Group

Observations	Positive Employer Response					Sample Size		
	NP	NB	NB - NP	B	B - NP	NP	NB	B
All Observations	0.313	0.258	-0.055 (0.011)	0.294	-0.019 (0.033)	3985	2695	1290
Implied Males	0.307	0.253	-0.053 (0.016)	0.291	-0.016 (0.040)	1994	1365	629
Implied Females	0.319	0.263	-0.056 (0.016)	0.297	-0.022 (0.038)	1991	1330	661
Democratic City	0.321	0.283	-0.038 (0.016)	0.311	-0.010 (0.035)	1999	1337	662
Republican City	0.305	0.233	-0.071 (0.016)	0.275	-0.029 (0.043)	1986	1358	628
Male-Dominated	0.289	0.235	-0.054 (0.019)	0.277	-0.011 (0.047)	1376	932	444
Non-Dominated	0.330	0.265	-0.065 (0.020)	0.299	-0.031 (0.044)	1305	864	441
Female-Dominated	0.321	0.276	-0.045 (0.020)	0.306	-0.015 (0.043)	1304	899	405
High Customer-Facing	0.304	0.244	-0.059 (0.021)	0.284	-0.020 (0.048)	1176	806	370
Medium Customer-Facing	0.293	0.260	-0.034 (0.021)	0.265	-0.028 (0.029)	1186	786	400
Low Customer-Facing	0.334	0.267	-0.066 (0.018)	0.323	-0.011 (0.053)	1623	1103	520
Equal Opportunity	0.327	0.290	-0.038 (0.026)	0.278	-0.049 (0.028)	822	563	259
Gender or Sexuality	0.299	0.261	-0.039 (0.033)	0.284	-0.016 (0.056)	481	326	155
Small Business	0.323	0.246	-0.077 (0.037)	0.382	0.059 (0.122)	399	276	123

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

Table 13: Differences in Positive Employer Response by Geography

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

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

Table 14: Differences in Positive Employer Response by Occupation

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

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

Table 15: Estimates of Discrimination Against Applicants who Disclose Pronouns

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Disclosing pronouns compared to not disclosing</i>					
Nonbinary Pronouns	-0.054 (0.008)	-0.054 (0.008)	-0.055 (0.008)	-0.054 (0.008)	-0.323 (0.044)
Binary Pronouns	-0.018 (0.012)	-0.017 (0.011)	-0.017 (0.011)	-0.017 (0.011)	-0.125 (0.066)
Observations	7970	7970	7970	7970	1244
<i>Panel B: Disclosing nonbinary compared to binary pronouns</i>					
Nonbinary Pronouns	-0.036 (0.015)	-0.036 (0.015)	-0.038 (0.014)	-0.037 (0.015)	
Observations	3985	3985	3985	3985	
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: Panel A reports marginal effects for the average applicant 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. Marginal effects are derived from the logistic regression described in equations (1). Panel B reports marginal effects for the average applicant associated with disclosing nonbinary “they/them” pronouns compared to applicants who disclose binary “he/him” or “she/her” pronouns congruent with name-implied sex. Marginal effects are derived from the logistic regression described in equation (2); only treated observations are included. In all panels, the dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 16: Estimates of Discrimination Against Applicants who Disclose Pronouns (Positive Employer Response Alternative)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Disclosing pronouns compared to not disclosing</i>					
Nonbinary Pronouns	-0.052 (0.008)	-0.053 (0.008)	-0.054 (0.008)	-0.053 (0.008)	-0.317 (0.044)
Binary Pronouns	-0.022 (0.012)	-0.020 (0.012)	-0.020 (0.012)	-0.020 (0.012)	-0.100 (0.066)
Observations	7970	7970	7970	7970	1244
<i>Panel B: Disclosing nonbinary compared to binary pronouns</i>					
Nonbinary Pronouns	-0.031 (0.016)	-0.032 (0.015)	-0.034 (0.015)	-0.032 (0.015)	
Observations	3985	3985	3985	3985	
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: Panel A reports marginal effects for the average applicant 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. Marginal effects are derived from the logistic regression described in equations (1). Panel B reports marginal effects for the average applicant associated with disclosing nonbinary “they/them” pronouns compared to applicants who disclose binary “he/him” or “she/her” pronouns congruent with name-implied sex. Marginal effects are derived from the logistic regression described in equation (2); only treated observations are included. In all panels, the dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 17: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Geographic Politics (Indicator)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include applications in Democratic geographies only</i>					
Nonbinary Pronouns	-0.037 (0.011)	-0.038 (0.011)	-0.037 (0.011)	-0.037 (0.011)	-0.241 (0.067)
Binary Pronouns	-0.010 (0.016)	-0.009 (0.016)	-0.010 (0.016)	-0.012 (0.016)	-0.046 (0.101)
Observations	3998	3998	3998	3998	590
<i>Panel B: Regressions include applications in Republican geographies only</i>					
Nonbinary Pronouns	-0.070 (0.011)	-0.071 (0.013)	-0.073 (0.011)	-0.072 (0.013)	-0.386 (0.059)
Binary Pronouns	-0.028 (0.016)	-0.025 (0.016)	-0.022 (0.016)	-0.022 (0.016)	-0.151 (0.086)
Observations	3972	3972	3972	3972	654
<i>Panel C: Regressions include all applications</i>					
Nonbinary Pronouns	-0.036 (0.011)	-0.036 (0.011)	-0.036 (0.011)	-0.035 (0.011)	-0.251 (0.066)
Nonbinary \times Republican	-0.037 (0.016)	-0.038 (0.016)	-0.039 (0.015)	-0.040 (0.016)	-0.148 (0.092)
Binary Pronouns	-0.009 (0.016)	-0.009 (0.016)	-0.009 (0.016)	-0.010 (0.016)	-0.061 (0.099)
Binary \times Republican	-0.019 (0.023)	-0.017 (0.023)	-0.015 (0.023)	-0.014 (0.023)	-0.122 (0.130)
Observations	7970	7970	7970	7970	1244
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A and B are derived from the logistic regression described in equation (1) with different data subsets; for Panel C from (4.1). 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.

Table 18: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Geographic Politics (Continuous)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regression does not include a squared Republican vote share term</i>					
Nonbinary Pronouns	-0.010 (0.031)	-0.007 (0.030)	-0.007 (0.029)	-0.005 (0.029)	-0.120 (0.192)
Nonbinary \times Vote Share	-0.092 (0.062)	-0.098 (0.059)	-0.100 (0.058)	-0.103 (0.059)	-0.407 (0.352)
Binary Pronouns	0.009 (0.047)	-0.001 (0.044)	-0.002 (0.044)	-0.005 (0.044)	0.100 (0.044)
Binary \times Vote Share	-0.057 (0.092)	-0.032 (0.088)	-0.031 (0.088)	-0.024 (0.088)	-0.465 (0.488)
Observations	7970	7970	7970	7970	1244
<i>Panel B: Regression does include a squared Republican vote share term</i>					
Nonbinary Pronouns	0.208 (0.108)	0.208 (0.107)	0.186 (0.109)	0.198 (0.108)	0.307 (0.210)
Nonbinary \times Vote Share	-1.009 (0.464)	-1.001 (0.465)	-0.907 (0.462)	-0.954 (0.463)	-2.837 (2.615)
Nonbinary \times Vote Share ²	0.900 (0.451)	0.882 (0.451)	0.789 (0.449)	0.831 (0.449)	2.372 (2.545)
Binary Pronouns	0.038 (0.177)	0.063 (0.181)	0.094 (0.184)	0.078 (0.182)	0.379 (0.340)
Binary \times Vote Share	-0.179 (0.692)	-0.295 (0.694)	-0.414 (0.690)	-0.359 (0.691)	-2.244 (3.617)
Binary \times Vote Share ²	0.122 (0.670)	0.256 (0.672)	0.374 (0.667)	0.327 (0.668)	1.767 (3.545)
Observations	7970	7970	7970	7970	1244
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects are derived from the logistic regression described in equation (4.1). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Vote share is Republican vote share. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 19: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions

	(A)	(B)	(C)	(D)	(E)
Nonbinary Pronouns	-0.019 (0.025)	-0.017 (0.025)	-0.017 (0.025)	-0.016 (0.025)	-0.150 (0.149)
Nonbinary \times Republican	-0.036 (0.016)	-0.037 (0.016)	-0.038 (0.015)	-0.038 (0.016)	-0.157 (0.091)
Nonbinary \times Implied Male	0.003 (0.016)	0.003 (0.016)	0.004 (0.016)	0.003 (0.016)	0.042 (0.090)
Nonbinary \times Relevant Experience	-0.005 (0.007)	-0.005 (0.007)	-0.007 (0.007)	-0.007 (0.007)	-0.038 (0.039)
Nonbinary \times Male-Dominated	0.002 (0.023)	0.000 (0.023)	0.006 (0.023)	0.003 (0.023)	0.100 (0.119)
Nonbinary \times Female-Dominated	0.027 (0.022)	0.018 (0.021)	0.024 (0.021)	0.022 (0.021)	0.161 (0.098)
Nonbinary \times High Customer-Facing	-0.028 (0.023)	-0.028 (0.022)	-0.032 (0.022)	-0.030 (0.022)	-0.207 (0.120)
Nonbinary \times Low Customer-Facing	-0.036 (0.019)	-0.036 (0.019)	-0.040 (0.019)	-0.038 (0.019)	-0.225 (0.106)
Nonbinary \times Equal Opportunity	0.021 (0.025)	0.028 (0.026)	0.026 (0.025)	0.029 (0.026)	-0.074 (0.149)
Nonbinary \times Gender Sexuality	0.004 (0.032)	-0.003 (0.031)	0.001 (0.032)	-0.002 (0.031)	0.082 (0.176)
Nonbinary \times Small Business	-0.029 (0.026)	-0.031 (0.026)	-0.025 (0.026)	-0.026 (0.026)	0.118 (0.132)
Binary Pronouns	-0.044 (0.034)	-0.043 (0.034)	-0.044 (0.034)	-0.043 (0.034)	-0.274 (0.176)
Binary \times Republican	-0.024 (0.023)	-0.023 (0.023)	-0.019 (0.023)	-0.019 (0.023)	-0.109 (0.131)
Binary \times Implied Male	0.003 (0.024)	0.002 (0.024)	0.001 (0.024)	0.001 (0.024)	-0.046 (0.141)
Binary \times Relevant Experience	0.007 (0.011)	0.006 (0.011)	0.009 (0.010)	0.008 (0.011)	0.080 (0.061)
Binary \times Male-Dominated	0.026 (0.034)	0.024 (0.034)	0.021 (0.033)	0.019 (0.033)	0.061 (0.192)
Binary \times Female-Dominated	0.007 (0.031)	0.011 (0.031)	0.008 (0.031)	0.006 (0.031)	0.007 (0.172)
Binary \times High Customer-Facing	0.020 (0.036)	0.027 (0.036)	0.028 (0.036)	0.030 (0.036)	0.347 (0.124)
Binary \times Low Customer-Facing	0.022 (0.030)	0.022 (0.030)	0.027 (0.030)	0.026 (0.030)	0.085 (0.162)
Binary \times Equal Opportunity	-0.053 (0.035)	-0.059 (0.035)	-0.062 (0.034)	-0.061 (0.035)	-0.046 (0.236)
Binary \times Gender Sexuality	0.043 (0.050)	0.048 (0.050)	0.049 (0.050)	0.047 (0.050)	0.056 (0.323)
Binary \times Small Business	0.096 (0.044)	0.098 (0.045)	0.082 (0.043)	0.084 (0.043)	-0.138 (0.201)
Observations	7970	7970	7970	7970	1244
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects derived from the logistic regression described in equation (5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 20: Heteroskedastic Logistic Discrimination Estimates (Neu-
mark’s Bias Correction)

	Nonbinary Pronouns	Binary Pronouns
<i>Panel A: Logistic coefficient estimates</i>		
Coefficient Estimate	-0.054 (0.008)	-0.017 (0.013)
<i>Panel B: Heteroskedastic logistic coefficient estimates</i>		
Total Estimate	-0.056 (0.008)	-0.016 (0.013)
Levels Estimate	-0.053 (0.021)	-0.030 (0.032)
Variance Estimate	-0.003 (0.020)	0.014 (0.032)
<i>Panel C: Tests</i>		
Overidentification test p-value (X_i coefficient ratios are equal for treatment and control)	0.927	0.357
Standard deviation of unobservables (treatment / control)	0.982	1.074
Test p-value (ratio of standard deviations = 1)	0.888	0.692
Observations	7970	7970
Resume Controls	X	X
Firm Controls		
Job Posting FE		

Note: This table reports marginal effects for the average applicant 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. Marginal effects are derived from the logistic and heteroskedastic logistic regressions described in equation (1) with resume controls. 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.

Table 21: Estimates of Discrimination Against Male and Female Applicants

	(A)	(B)	(C)	(D)
Implied Male	-0.035 (0.015)	-0.044 (0.021)	-0.048 (0.020)	-0.047 (0.021)
Implied Male \times Female-Dominated	-0.018 (0.019)	-0.009 (0.031)	-0.008 (0.031)	-0.004 (0.031)
Implied Female \times Male-Dominated	-0.092 (0.017)	-0.108 (0.024)	-0.111 (0.023)	-0.109 (0.024)
Nonbinary Pronouns	-0.053 (0.008)	-0.054 (0.008)	-0.055 (0.008)	-0.054 (0.008)
Binary Pronouns	-0.019 (0.011)	-0.018 (0.011)	-0.017 (0.011)	-0.017 (0.011)
Observations	7970	7970	7970	7970
Resume Controls		X		X
Firm Controls			X	X
Job Posting FE				

Note: This table reports marginal effects for the average applicant associated with having a name that is implied male versus female. Marginal effects for Panels A to C are derived from the logistic regression described in equation (6). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

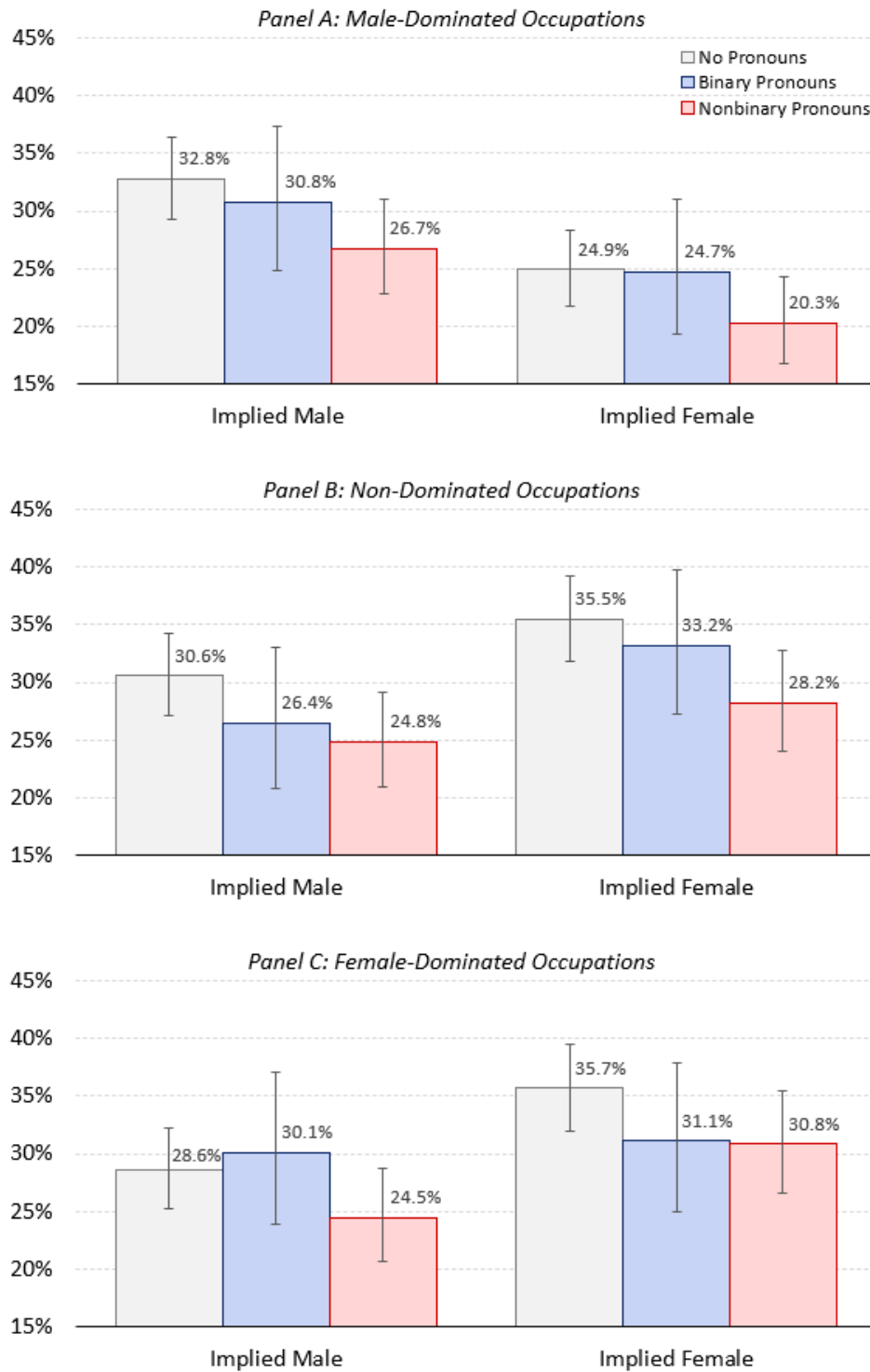


Figure 4: Positive Employer Response Rates by Implied Sex and Pronouns Disclosed

6 References

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A Appendix

All remaining empirical results are presented here, including:

- **Differences by geographic politics:** Implied discrimination stemming from Panel B of Table 18, given Republican vote share, is reported in Table 22.
- **Differences by experience:** Results of equation (1) when isolating applicants who do and do not have “relevant” experience, and of equation (4.2) are reported in Tables 23.
- **Differences by implied sex:** Results of equation (1) when isolating applicants who are implied male and female, and of equation (4.3) are reported in Table 24.
- **Differences by occupation male-female worker composition:** Results of equation (1) when isolating applications to occupations with different male-female worker compositions, and of equation (4.4) with indicator and continuous interactions are reported in Tables 25 and 26.
- **Differences by occupation customer interaction:** Results of equation (1) when isolating applications to occupations with different customer interaction levels, and of equation (4.5) with indicator and continuous interactions are reported in Tables 27 and 28.
- **Differences by job posting text:** Results of equation (1) when isolating applications to jobs which contain key words and phrases, and of equation (4.6) are reported in Table 29.
- **All interactions:** Results of equation (5) using continuous interactions were reported in Tables 30 and 31.

Tables and Figures

Table 22: Implied Average Discrimination Associated With Nonbinary Pronoun Disclosure by Geographic Republican Vote Share

Vote Share	Implied Discrimination by Regression Specification			
	(A)	(B)	(C)	(D)
30%	-1.4%	-1.3%	-1.6%	-1.3%
35%	-3.5%	-3.4%	-3.5%	-3.4%
40%	-5.2%	-5.1%	-5.1%	-5.1%
45%	-6.4%	-6.4%	-6.3%	-6.3%
50%	-7.2%	-7.2%	-7.1%	-7.1%
55%	-7.5%	-7.6%	-7.5%	-7.5%
60%	-7.4%	-7.5%	-7.5%	-7.5%
65%	-6.8%	-7.0%	-7.1%	-7.1%
70%	-5.8%	-6.1%	-6.3%	-6.3%
Observations	7970	7970	7970	7970
Resume Controls		X		X
Firm Controls			X	X
Job Posting FE				

Note: This table reports implied discrimination associated with disclosing nonbinary “they/them” pronouns compared to not disclosing pronouns, based on geographic (CBSA level) Republican vote share. Implied discrimination is calculated from coefficient estimates reported in Panel B of Table 18.

Table 23: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Experience

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include applicants with relevant experience only</i>					
Nonbinary Pronouns	-0.058 (0.011)	-0.060 (0.012)	-0.061 (0.010)	-0.061 (0.012)	-0.301 (0.055)
Binary Pronouns	-0.023 (0.016)	-0.022 (0.016)	-0.020 (0.016)	-0.020 (0.016)	-0.127 (0.081)
Observations	4610	4610	4610	4610	796
<i>Panel B: Regressions include applicants with no relevant experience only</i>					
Nonbinary Pronouns	-0.047 (0.011)	-0.048 (0.012)	-0.047 (0.011)	-0.047 (0.012)	-0.353 (0.074)
Binary Pronouns	-0.013 (0.017)	-0.012 (0.017)	-0.014 (0.016)	-0.014 (0.016)	-0.077 (0.121)
Observations	3360	3360	3360	3360	448
<i>Panel C: Regressions include all applicants (no squared term)</i>					
Nonbinary Pronouns	-0.047 (0.011)	-0.048 (0.011)	-0.047 (0.011)	-0.047 (0.011)	-0.291 (0.064)
Nonbinary \times Years Relevant	-0.006 (0.007)	-0.006 (0.007)	-0.007 (0.007)	-0.007 (0.007)	-0.029 (0.039)
Binary Pronouns	-0.026 (0.016)	-0.022 (0.017)	-0.025 (0.016)	-0.025 (0.016)	-0.199 (0.095)
Binary \times Years Relevant	0.007 (0.011)	0.005 (0.011)	0.008 (0.010)	0.007 (0.011)	0.066 (0.062)
Observations	7970	7970	7970	7970	1244
<i>Panel D: Regressions include all applicants (with a squared term)</i>					
Nonbinary Pronouns	-0.037 (0.012)	-0.052 (0.012)	-0.052 (0.012)	-0.051 (0.012)	-0.341 (0.067)
Nonbinary \times Years Relevant	0.010 (0.020)	0.009 (0.019)	0.008 (0.019)	0.008 (0.019)	0.170 (0.108)
Nonbinary \times Years Relevant ²	-0.005 (0.006)	-0.005 (0.006)	-0.005 (0.006)	-0.005 (0.006)	-0.067 (0.034)
Binary Pronouns	-0.018 (0.018)	-0.015 (0.018)	-0.017 (0.018)	-0.018 (0.018)	-0.116 (0.109)
Binary \times Years Relevant	-0.023 (0.028)	-0.020 (0.028)	-0.021 (0.028)	-0.018 (0.028)	-0.224 (0.178)
Binary \times Years Relevant ²	0.010 (0.009)	0.009 (0.009)	0.010 (0.009)	0.008 (0.009)	0.102 (0.061)
Observations	7970	7970	7970	7970	1244
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A and B are derived from the logistic regression described in equation (1) with different data subsets; for Panels C and D from (4.2). 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.

Table 24: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Implied Sex

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include implied male applicants only</i>					
Nonbinary Pronouns	-0.053 (0.011)	-0.053 (0.012)	-0.053 (0.011)	-0.053 (0.012)	-0.301 (0.062)
Binary Pronouns	-0.015 (0.016)	-0.017 (0.016)	-0.017 (0.016)	-0.018 (0.016)	-0.176 (0.096)
Observations	3984	3984	3984	3984	604
<i>Panel B: Regressions include implied female applicants only</i>					
Nonbinary Pronouns	-0.055 (0.011)	-0.056 (0.012)	-0.058 (0.011)	-0.057 (0.012)	-0.342 (0.063)
Binary Pronouns	-0.022 (0.016)	-0.019 (0.016)	-0.016 (0.016)	-0.018 (0.016)	-0.099 (0.087)
Observations	3986	3986	3986	3986	630
<i>Panel C: Regressions include all applications</i>					
Nonbinary Pronouns	-0.054 (0.011)	-0.056 (0.011)	-0.057 (0.011)	-0.056 (0.011)	-0.345 (0.060)
Nonbinary \times Implied Male	0.001 (0.016)	0.003 (0.016)	0.003 (0.016)	0.004 (0.016)	0.050 (0.089)
Binary Pronouns	-0.021 (0.016)	-0.018 (0.016)	-0.017 (0.016)	-0.017 (0.016)	-0.084 (0.088)
Binary \times Implied Male	0.006 (0.024)	0.002 (0.024)	0.001 (0.024)	0.001 (0.023)	-0.091 (0.133)
Observations	7970	7970	7970	7970	1234
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A and B are derived from the logistic regression described in equation (1) with different data subsets; for Panel C from (4.3) 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.

Table 25: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Worker Composition (Indicator)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include applications to male-dominated occupations only</i>					
Nonbinary Pronouns	-0.053 (0.013)	-0.057 (0.014)	-0.052 (0.013)	-0.056 (0.014)	-0.324 (0.080)
Binary Pronouns	-0.011 (0.019)	-0.010 (0.019)	-0.013 (0.019)	-0.013 (0.018)	-0.175 (0.116)
Observations	2752	2752	2752	2752	394
<i>Panel B: Regressions include applications to non-dominated occupations only</i>					
Nonbinary Pronouns	-0.064 (0.014)	-0.064 (0.014)	-0.067 (0.014)	-0.065 (0.015)	-0.407 (0.082)
Binary Pronouns	-0.030 (0.020)	-0.030 (0.020)	-0.024 (0.020)	-0.022 (0.020)	-0.008 (0.115)
Observations	2610	2610	2610	2610	442
<i>Panel C: Regressions include applications to female-dominated occupations only</i>					
Nonbinary Pronouns	-0.045 (0.014)	-0.047 (0.014)	-0.047 (0.013)	-0.047 (0.014)	-0.292 (0.077)
Binary Pronouns	-0.015 (0.022)	-0.018 (0.021)	-0.011 (0.021)	-0.019 (0.021)	-0.128 (0.110)
Observations	2608	2608	2608	2608	398
<i>Panel D: Regressions include all applications</i>					
Nonbinary Pronouns	-0.063 (0.014)	-0.059 (0.014)	-0.064 (0.014)	-0.061 (0.014)	-0.392 (0.065)
Nonbinary \times Male-Dominated	0.007 (0.021)	0.003 (0.020)	0.010 (0.020)	0.005 (0.020)	0.110 (0.103)
Nonbinary \times Female-Dominated	0.020 (0.021)	0.014 (0.020)	0.018 (0.020)	0.017 (0.020)	0.140 (0.100)
Binary Pronouns	-0.029 (0.020)	-0.027 (0.019)	-0.025 (0.019)	-0.023 (0.019)	-0.041 (0.122)
Binary \times Male-Dominated	0.0180 (0.0292)	0.0177 (0.0289)	0.0115 (0.0285)	0.0118 (0.0285)	-0.1624 (0.162)
Binary \times Female-Dominated	0.015 (0.030)	0.014 (0.030)	0.014 (0.030)	0.009 (0.030)	-0.089 (0.158)
Observations	7970	7970	7970	7970	1234
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A to C are derived from the logistic regression described in equation (1) with different data subsets; for Panel D from (4.4). 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.

Table 26: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Worker Composition (Continuous)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regression does not include a squared percent male term</i>					
Nonbinary Pronouns	-0.048 (0.015)	-0.049 (0.015)	-0.052 (0.015)	-0.050 (0.015)	-0.301 (0.085)
Nonbinary \times Percent Male	-0.0122 (0.0250)	-0.0098 (0.0258)	-0.0054 (0.0260)	-0.0095 (0.0258)	-0.0461 (0.1505)
Binary Pronouns	-0.014 (0.022)	-0.015 (0.023)	-0.008 (0.023)	-0.013 (0.023)	-0.093 (0.118)
Binary \times Percent Male	-0.007 (0.037)	-0.004 (0.038)	-0.016 (0.038)	-0.007 (0.037)	-0.064 (0.204)
Observations	7970	7970	7970	7970	1234
<i>Panel B: Regression does include a squared percent male term</i>					
Nonbinary Pronouns	-0.037 (0.021)	-0.041 (0.022)	-0.040 (0.022)	-0.038 (0.022)	-0.251 (0.124)
Nonbinary \times Percent Male	-0.087 (0.107)	-0.068 (0.111)	-0.085 (0.111)	-0.083 (0.111)	-0.381 (0.605)
Nonbinary \times Percent Male ²	0.074 (0.105)	0.058 (0.107)	0.080 (0.107)	0.073 (0.107)	0.335 (0.591)
Binary Pronouns	-0.010 (0.032)	-0.012 (0.033)	-0.009 (0.033)	-0.017 (0.033)	-0.167 (0.162)
Binary \times Percent Male	-0.037 (0.154)	-0.019 (0.158)	-0.012 (0.159)	0.016 (0.157)	0.465 (0.916)
Binary \times Percent Male ²	0.0290 (0.1495)	0.0145 (0.1513)	-0.0037 (0.1522)	-0.0227 (0.1511)	-0.5378 (0.908)
Observations	7970	7970	7970	7970	1234
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects derived from the logistic regression described in equation (4.4). 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.

Table 27: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Customer Interaction (Indicator)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include applications to high customer-facing occupations only</i>					
Nonbinary Pronouns	-0.058 (0.015)	-0.059 (0.016)	-0.063 (0.014)	-0.061 (0.016)	-0.384 (0.084)
Binary Pronouns	-0.019 (0.022)	-0.017 (0.021)	-0.010 (0.022)	-0.012 (0.021)	0.088 (0.119)
Observations	2352	2352	2352	2352	402
<i>Panel B: Regressions include applications to medium customer-facing occupations only</i>					
Nonbinary Pronouns	-0.033 (0.014)	-0.031 (0.014)	-0.032 (0.014)	-0.030 (0.014)	-0.167 (0.090)
Binary Pronouns	-0.028 (0.021)	-0.028 (0.021)	-0.031 (0.020)	-0.031 (0.021)	-0.256 (0.123)
Observations	2372	2372	2372	2372	348
<i>Panel C: Regressions include applications to low customer-facing occupations only</i>					
Nonbinary Pronouns	-0.066 (0.012)	-0.065 (0.013)	-0.068 (0.012)	-0.065 (0.013)	-0.359 (0.069)
Binary Pronouns	-0.010 (0.018)	-0.011 (0.018)	-0.007 (0.018)	-0.010 (0.018)	-0.157 (0.100)
Observations	3246	3246	3246	3246	494
<i>Panel D: Regressions include all applications</i>					
Nonbinary Pronouns	-0.034 (0.015)	-0.034 (0.014)	-0.032 (0.014)	-0.033 (0.014)	-0.168 (0.089)
Nonbinary \times High Customer-Facing	-0.026 (0.021)	-0.024 (0.021)	-0.031 (0.020)	-0.027 (0.021)	-0.220 (0.111)
Nonbinary \times Low Customer-Facing	-0.029 (0.018)	-0.031 (0.019)	-0.034 (0.018)	-0.032 (0.019)	-0.200 (0.107)
Binary Pronouns	-0.028 (0.021)	-0.028 (0.021)	-0.032 (0.021)	-0.031 (0.021)	-0.254 (0.102)
Binary \times High Customer-Facing	0.009 (0.032)	0.015 (0.032)	0.021 (0.032)	0.021 (0.032)	0.335 (0.116)
Binary \times Low Customer-Facing	0.019 (0.029)	0.019 (0.029)	0.026 (0.029)	0.023 (0.029)	0.084 (0.155)
Observations	7970	7970	7970	7970	1244
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A to C are derived from the logistic regression described in equation (1) with different data subsets; for Panel D from (4.5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 28: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Customer Interaction (Continuous)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regression does not include a squared O*NET customer interaction score term</i>					
Nonbinary Pronouns	-0.053 (0.024)	-0.055 (0.024)	-0.053 (0.024)	-0.054 (0.024)	-0.273 (0.126)
Nonbinary \times O*NET Score	0.0000 (0.0004)	0.0000 (0.0004)	0.0000 (0.0004)	0.0000 (0.0004)	-0.0009 (0.0021)
Binary Pronouns	-0.017 (0.034)	-0.018 (0.034)	-0.019 (0.033)	-0.019 (0.033)	-0.410 (0.120)
Binary \times O*NET Score	0.0000 (0.0006)	0.0000 (0.0006)	0.0000 (0.0006)	0.0000 (0.0006)	0.0066 (0.0035)
Observations	7970	7970	7970	7970	1244
<i>Panel B: Regression does include a squared O*NET customer interaction score term</i>					
Nonbinary Pronouns	-0.104 (0.064)	-0.098 (0.068)	-0.109 (0.066)	-0.101 (0.067)	-0.546 (0.120)
Nonbinary \times O*NET Score	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.016 (0.013)
Nonbinary \times O*NET Score ²	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0001 (0.0001)
Binary Pronouns	-0.048 (0.077)	-0.028 (0.084)	-0.037 (0.081)	-0.024 (0.084)	0.261 (0.414)
Binary \times O*NET Score	0.0012 (0.0029)	0.0004 (0.0030)	0.0007 (0.0030)	0.0002 (0.0030)	-0.0216 (0.0195)
Binary \times O*NET Score ²	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	0.0002 (0.0002)
Observations	7970	7970	7970	7970	1244
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects are derived from the logistic regression described in equation (4.5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 29: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Job Posting Text

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include applications to job postings mentioning “equal opportunity”</i>					
Nonbinary Pronouns	-0.037 (0.017)	-0.041 (0.018)	-0.036 (0.017)	-0.039 (0.018)	-0.349 (0.093)
Binary Pronouns	-0.048 (0.026)	-0.050 (0.027)	-0.051 (0.025)	-0.054 (0.026)	-0.101 (0.163)
Observations	1644	1644	1644	1644	240
<i>Panel B: Regressions include applications to job postings mentioning gender or sexuality</i>					
Nonbinary Pronouns	-0.038 (0.022)	-0.043 (0.023)	-0.041 (0.022)	-0.043 (0.023)	-0.280 (0.130)
Binary Pronouns	-0.015 (0.032)	-0.009 (0.033)	-0.009 (0.032)	-0.015 (0.032)	0.152 (0.158)
Observations	962	962	962	962	130
<i>Panel C: Regressions include applications to job postings mentioning small business</i>					
Nonbinary Pronouns	-0.080 (0.027)	-0.079 (0.028)	-0.070 (0.025)	-0.069 (0.028)	-0.267 (0.155)
Binary Pronouns	0.056 (0.039)	0.059 (0.041)	0.035 (0.038)	0.039 (0.039)	0.026 (0.202)
Observations	798	798	798	798	132
<i>Panel D: Regressions include applications to job postings mentioning none of the above</i>					
Nonbinary Pronouns	-0.056 (0.009)	-0.056 (0.010)	-0.057 (0.009)	-0.057 (0.010)	-0.343 (0.055)
Binary Pronouns	-0.016 (0.014)	-0.015 (0.014)	-0.013 (0.014)	-0.014 (0.014)	-0.102 (0.079)
Observations	5596	5596	5596	5596	874
<i>Panel E: Regressions include all applications</i>					
Nonbinary Pronouns	-0.057 (0.010)	-0.057 (0.010)	-0.059 (0.009)	-0.058 (0.010)	-0.336 (0.051)
Nonbinary \times Equal Opportunity	0.025 (0.026)	0.029 (0.026)	0.029 (0.026)	0.030 (0.026)	-0.060 (0.148)
Nonbinary \times Gender or Sexuality	-0.002 (0.032)	-0.003 (0.031)	-0.004 (0.031)	-0.003 (0.031)	0.097 (0.175)
Nonbinary \times Small Business	-0.025 (0.028)	-0.029 (0.026)	-0.021 (0.027)	-0.024 (0.027)	0.140 (0.133)
Binary Pronouns	-0.020 (0.014)	-0.019 (0.013)	-0.016 (0.014)	-0.017 (0.013)	-0.102 (0.078)
Binary \times Equal Opportunity	-0.060 (0.036)	-0.058 (0.035)	-0.066 (0.033)	-0.061 (0.034)	-0.088 (0.235)
Binary \times Gender or Sexuality	0.055 (0.050)	0.049 (0.050)	0.059 (0.050)	0.049 (0.050)	0.111 (0.312)
Binary \times Small Business	0.082 (0.043)	0.094 (0.044)	0.074 (0.042)	0.080 (0.043)	-0.157 (0.199)
Observations	7970	7970	7970	7970	1244
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A to D are derived from the logistic regression described in equation (1) with different data subsets; for Panel E from (4.6). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 30: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions (Continuous, No Squares)

	(A)	(B)	(C)	(D)	(E)
Nonbinary Pronouns	0.004 (0.045)	-0.002 (0.044)	0.001 (0.044)	0.001 (0.044)	-0.028 (0.246)
Nonbinary \times Implied Male	0.002 (0.016)	0.003 (0.016)	0.004 (0.016)	0.003 (0.016)	0.038 (0.091)
Nonbinary \times Vote Share	-0.090 (0.062)	-0.093 (0.059)	-0.097 (0.058)	-0.098 (0.059)	-0.393 (0.350)
Nonbinary \times O*NET Score	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.001 (0.002)
Nonbinary \times Percent Male	-0.018 (0.026)	-0.010 (0.026)	-0.010 (0.027)	-0.010 (0.026)	-0.055 (0.154)
Nonbinary \times Relevant Experience	-0.006 (0.007)	-0.006 (0.007)	-0.007 (0.007)	-0.007 (0.007)	-0.030 (0.039)
Nonbinary \times Equal Opportunity	0.022 (0.026)	0.028 (0.026)	0.026 (0.025)	0.029 (0.026)	-0.066 (0.148)
Nonbinary \times Gender Sexuality	0.000 (0.032)	-0.005 (0.031)	-0.002 (0.031)	-0.005 (0.031)	0.081 (0.174)
Nonbinary \times Small Business	-0.027 (0.027)	-0.030 (0.026)	-0.024 (0.027)	-0.025 (0.026)	0.137 (0.133)
Binary Pronouns	0.003 (0.067)	-0.004 (0.063)	-0.004 (0.063)	-0.007 (0.064)	-0.343 (0.278)
Binary \times Implied Male	0.004 (0.024)	0.003 (0.024)	0.001 (0.024)	0.001 (0.024)	-0.046 (0.145)
Binary \times Vote Share	-0.062 (0.092)	-0.042 (0.089)	-0.034 (0.088)	-0.036 (0.089)	-0.338 (0.499)
Binary \times O*NET Score	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.007 (0.004)
Binary \times Percent Male	0.004 (0.038)	-0.002 (0.039)	-0.005 (0.039)	-0.004 (0.039)	0.018 (0.212)
Binary \times Relevant Experience	0.007 (0.011)	0.006 (0.011)	0.009 (0.010)	0.008 (0.011)	0.070 (0.061)
Binary \times Equal Opportunity	-0.054 (0.035)	-0.059 (0.035)	-0.062 (0.034)	-0.061 (0.035)	-0.096 (0.229)
Binary \times Gender Sexuality	0.045 (0.050)	0.047 (0.050)	0.049 (0.050)	0.047 (0.050)	0.111 (0.314)
Binary \times Small Business	0.089 (0.044)	0.095 (0.044)	0.078 (0.043)	0.081 (0.043)	-0.192 (0.187)
Observations	7970	7970	7970	7970	1244
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects derived from the logistic regression described in equation (5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 31: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions (Continuous, Including Squares)

	(A)	(B)	(C)	(D)	(E)
Nonbinary Pronouns	0.178 (0.134)	0.172 (0.138)	0.146 (0.139)	0.160 (0.137)	-0.002 (0.771)
Nonbinary \times Implied Male	0.002 (0.016)	0.003 (0.016)	0.003 (0.016)	0.003 (0.016)	0.040 (0.089)
Nonbinary \times Vote Share	-1.039 (0.461)	-0.995 (0.464)	-0.936 (0.460)	-0.941 (0.463)	-2.533 (2.601)
Nonbinary \times Vote Share ²	0.925 (0.448)	0.880 (0.450)	0.819 (0.447)	0.824 (0.449)	2.078 (2.524)
Nonbinary \times O*NET Score	0.002 (0.002)	0.001 (0.003)	0.002 (0.003)	0.002 (0.003)	0.015 (0.013)
Nonbinary \times O*NET Score ²	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Nonbinary \times Percent Male	-0.052 (0.116)	-0.043 (0.123)	-0.055 (0.122)	-0.058 (0.122)	-0.142 (0.660)
Nonbinary \times Percent Male ²	0.039 (0.114)	0.035 (0.119)	0.049 (0.119)	0.051 (0.119)	0.119 (0.653)
Nonbinary \times Relevant Experience	0.012 (0.020)	0.010 (0.019)	0.009 (0.019)	0.008 (0.019)	0.159 (0.108)
Nonbinary \times Relevant Experience ²	-0.006 (0.006)	-0.005 (0.006)	-0.005 (0.006)	-0.005 (0.006)	-0.063 (0.034)
Nonbinary \times Equal Opportunity	0.022 (0.026)	0.028 (0.026)	0.025 (0.025)	0.029 (0.026)	-0.060 (0.146)
Nonbinary \times Gender Sexuality	0.001 (0.032)	-0.004 (0.031)	0.000 (0.032)	-0.003 (0.031)	0.078 (0.175)
Nonbinary \times Small Business	-0.030 (0.026)	-0.032 (0.026)	-0.025 (0.027)	-0.027 (0.026)	0.103 (0.137)
Binary Pronouns	0.010 (0.208)	0.072 (0.226)	0.066 (0.220)	0.078 (0.224)	0.470 (0.112)
Binary \times Implied Male	0.005 (0.024)	0.003 (0.024)	0.001 (0.024)	0.002 (0.024)	-0.043 (0.144)
Binary \times Vote Share	-0.191 (0.694)	-0.382 (0.702)	-0.417 (0.694)	-0.443 (0.700)	-2.734 (3.631)
Binary \times Vote Share ²	0.140 (0.672)	0.331 (0.680)	0.374 (0.671)	0.398 (0.677)	2.311 (3.574)
Binary \times O*NET Score	0.001 (0.003)	0.000 (0.003)	0.001 (0.003)	0.001 (0.003)	-0.021 (0.022)
Binary \times O*NET Score ²	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Binary \times Percent Male	0.003 (0.167)	0.010 (0.175)	0.040 (0.174)	0.049 (0.174)	-0.530 (1.038)
Binary \times Percent Male ²	-0.003 (0.164)	-0.010 (0.169)	-0.043 (0.169)	-0.052 (0.169)	0.548 (1.031)
Binary \times Relevant Experience	-0.029 (0.028)	-0.023 (0.028)	-0.024 (0.028)	-0.021 (0.028)	-0.162 (0.186)
Binary \times Relevant Experience ²	0.012 (0.009)	0.010 (0.009)	0.011 (0.009)	0.010 (0.009)	0.081 (0.063)
Binary \times Equal Opportunity	-0.054 (0.035)	-0.059 (0.035)	-0.061 (0.034)	-0.061 (0.035)	-0.093 (0.232)
Binary \times Gender Sexuality	0.045 (0.050)	0.047 (0.050)	0.048 (0.050)	0.046 (0.050)	0.024 (0.355)
Binary \times Small Business	0.094 (0.044)	0.097 (0.044)	0.080 (0.043)	0.084 (0.043)	-0.156 (0.196)
Observations	7970	7970	7970	7970	1244
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects derived from the logistic regression described in equation (5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

B Appendix

All results are presented here, using an alternative definition of positive employer response (any response that could be interpreted as positive was categorized as such). This includes:

- **Main results:** Figures 3 and 4 are replicated using the alternative definition of positive employer response, and reported in Figures 5 and 6. Tables 12, 13, 14, 17, 18, 19, 20 and 21 are replicated and reported in Tables 32, 33, 34, 35, 36, 37, 38 and 39.
- **Differences by geographic politics:** Implied discrimination stemming from Panel B of Table 36, given Republican vote share, is reported in Table 40.
- **Differences by experience:** Results of equation (1) when isolating applicants who do and do not have “relevant” experience, and of equation (4.2) are reported in Table 41.
- **Differences by implied sex:** Results of equation (1) when isolating applicants who are implied male and female, and of equation (4.3) are reported in Table 42.
- **Differences by occupation male-female worker composition:** Results of equation (1) when isolating applications to occupations with different male-female worker compositions, and of equation (4.4) with indicator and continuous interactions are reported in Tables 43 and 44.
- **Differences by occupation customer interaction:** Results of equation (1) when isolating applications to occupations with different customer interaction levels, and of equation (4.5) with indicator and continuous interactions are reported in Tables 45 and 46.
- **Differences by job posting text:** Results of equation (1) when isolating applications to jobs which contain key words and phrases, and of equation (4.6) are reported in Tables 47.
- **All interactions:** Results of equation (5) using continuous interactions were reported in Tables 48 and 49.

Tables and Figures

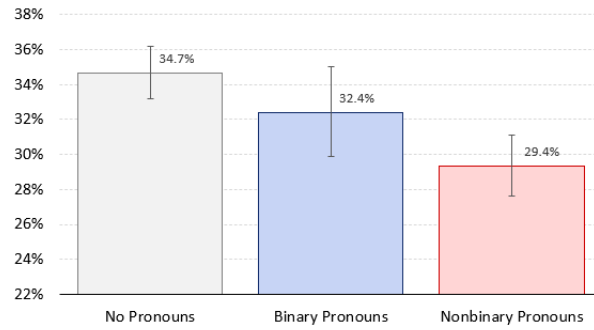


Figure 5: Positive Employer Response: Pronoun Disclosure

Table 32: Differences in Positive Employer Response by Group

Observations	Positive Employer Response					Sample Size		
	NP	NB	NB - NP	B	B - NP	NP	NB	B
All Observations	0.347	0.294	-0.053 (0.012)	0.324	-0.023 (0.031)	3985	2695	1290
Implied Males	0.341	0.290	-0.051 (0.017)	0.323	-0.018 (0.039)	1994	1365	629
Implied Females	0.352	0.297	-0.055 (0.017)	0.325	-0.027 (0.036)	1991	1330	661
Democratic City	0.357	0.319	-0.038 (0.017)	0.344	-0.012 (0.035)	1999	1337	662
Republican City	0.336	0.269	-0.068 (0.016)	0.303	-0.034 (0.039)	1986	1358	628
Male-Dominated	0.320	0.262	-0.059 (0.020)	0.311	-0.010 (0.051)	1376	932	444
Non-Dominated	0.359	0.30	-0.059 (0.021)	0.315	-0.043 (0.034)	1305	864	441
Female-Dominated	0.362	0.320	-0.042 (0.021)	0.348	-0.014 (0.042)	1304	899	405
High Customer-Facing	0.338	0.285	-0.053 (0.022)	0.311	-0.028 (0.042)	1176	806	370
Medium Customer-Facing	0.327	0.293	-0.035 (0.022)	0.308	-0.020 (0.035)	1186	786	400
Low Customer-Facing	0.367	0.30	-0.067 (0.019)	0.346	-0.020 (0.048)	1623	1103	520
Equal Opportunity	0.345	0.309	-0.036 (0.026)	0.293	-0.052 (0.026)	822	563	259
Gender or Sexuality	0.316	0.285	-0.031 (0.034)	0.303	-0.013 (0.054)	481	326	155
Small Business	0.368	0.279	-0.089 (0.038)	0.423	0.054 (0.127)	399	276	123

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

Table 33: Differences in Positive Employer Response by Geography

Observations	Positive Employer Response					Sample Size		
	NP	NB	NB - NP	B	B - NP	NP	NB	B
Washington	0.333	0.282	-0.051 (0.020)	0.310	-0.023 (0.041)	1323	910	413
Colorado	0.352	0.294	-0.058 (0.021)	0.330	-0.022 (0.045)	1325	882	443
Utah	0.355	0.305	-0.050 (0.021)	0.332	-0.023 (0.041)	1337	903	434
Seattle, WA	0.372	0.342	-0.030 (0.030)	0.365	-0.007 (0.051)	664	453	211
Spokane, WA	0.294	0.223	-0.071 (0.027)	0.252	-0.042 (0.052)	659	457	202
Denver, CO	0.359	0.326	-0.033 (0.030)	0.339	-0.020 (0.045)	666	442	224
Colorado Springs, CO	0.344	0.261	-0.083 (0.029)	0.320	-0.025 (0.068)	659	440	219
Salt Lake City, UT	0.339	0.287	-0.052 (0.029)	0.330	-0.009 (0.060)	669	442	227
Provo, UT	0.370	0.321	-0.049 (0.030)	0.333	-0.036 (0.046)	668	461	207

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

Table 34: Differences in Positive Employer Response by Occupation

Observations	Positive Employer Response					Sample Size		
	NP	NB	NB - NP	B	B - NP	NP	NB	B
Administrative Assistant	0.188	0.136	-0.052 (0.042)	0.225	0.037 (0.107)	218	147	71
Construction Worker	0.223	0.206	-0.018 (0.047)	0.243	0.020 (0.081)	215	141	74
Receptionist	0.261	0.234	-0.027 (0.041)	0.255	-0.006 (0.065)	299	201	98
Server	0.285	0.212	-0.073 (0.051)	0.265	-0.020 (0.094)	200	132	68
Janitor	0.327	0.265	-0.062 (0.050)	0.364	0.036 (0.128)	217	162	55
Assembler	0.319	0.276	-0.043 (0.061)	0.246	-0.073 (0.056)	166	105	61
Landscaper	0.352	0.262	-0.090 (0.052)	0.324	-0.029 (0.102)	213	145	68
Truck Driver	0.346	0.288	-0.058 (0.038)	0.326	-0.020 (0.069)	396	267	129
Warehouse Worker	0.328	0.263	-0.066 (0.041)	0.305	-0.023 (0.074)	335	217	118
Housekeeper	0.371	0.351	-0.020 (0.053)	0.359	-0.012 (0.071)	229	151	78
Cook	0.341	0.313	-0.028 (0.042)	0.294	-0.047 (0.042)	346	227	119
Retail Sales	0.386	0.314	-0.072 (0.035)	0.343	-0.043 (0.060)	500	334	166
Cashier	0.395	0.360	-0.036 (0.058)	0.395	-0.001 (0.106)	177	139	38
Baker	0.505	0.394	-0.111 (0.086)	0.519	0.013 (0.180)	93	66	27
Certified Nursing Assistant	0.520	0.452	-0.068 (0.042)	0.475	-0.045 (0.067)	381	261	120

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

Table 35: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Geographic Politics (Indicator)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include applications in Democratic geographies only</i>					
Nonbinary Pronouns	-0.038 (0.011)	-0.039 (0.011)	-0.038 (0.011)	-0.038 (0.011)	-0.254 (0.066)
Binary Pronouns	-0.012 (0.017)	-0.012 (0.017)	-0.011 (0.017)	-0.014 (0.017)	0.001 (0.096)
Observations	3998	3998	3998	3998	614
<i>Panel B: Regressions include applications in Republican geographies only</i>					
Nonbinary Pronouns	-0.066 (0.011)	-0.067 (0.012)	-0.069 (0.011)	-0.067 (0.012)	-0.365 (0.058)
Binary Pronouns	-0.032 (0.017)	-0.028 (0.017)	-0.027 (0.017)	-0.026 (0.017)	-0.151 (0.088)
Observations	3972	3972	3972	3972	670
<i>Panel C: Regressions include all applications</i>					
Nonbinary Pronouns	-0.037 (0.011)	-0.037 (0.011)	-0.037 (0.011)	-0.036 (0.011)	-0.265 (0.065)
Nonbinary \times Republican	-0.032 (0.016)	-0.034 (0.016)	-0.034 (0.016)	-0.035 (0.016)	-0.106 (0.092)
Binary Pronouns	-0.012 (0.017)	-0.011 (0.016)	-0.011 (0.016)	-0.012 (0.016)	-0.019 (0.095)
Binary \times Republican	-0.022 (0.024)	-0.018 (0.024)	-0.019 (0.024)	-0.015 (0.024)	-0.159 (0.124)
Observations	7970	7970	7970	7970	1284
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A and B are derived from the logistic regression described in equation (1) with different data subsets; for Panel C from (4.1). 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.

Table 36: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Geographic Politics (Continuous)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regression does not include a squared Republican vote share term</i>					
Nonbinary Pronouns	-0.011 (0.032)	-0.007 (0.030)	-0.008 (0.030)	-0.006 (0.030)	-0.145 (0.186)
Nonbinary \times Vote Share	-0.086 (0.063)	-0.093 (0.060)	-0.094 (0.059)	-0.097 (0.059)	-0.347 (0.343)
Binary Pronouns	0.015 (0.049)	0.000 (0.046)	0.004 (0.046)	-0.003 (0.046)	0.213 (0.197)
Binary \times Vote Share	-0.075 (0.094)	-0.041 (0.091)	-0.049 (0.091)	-0.035 (0.090)	-0.682 (0.482)
Observations	7970	7970	7970	7970	1284
<i>Panel B: Regression does include a squared Republican vote share term</i>					
Nonbinary Pronouns	0.200 (0.106)	0.198 (0.106)	0.177 (0.108)	0.191 (0.106)	0.325 (0.170)
Nonbinary \times Republican Vote Share	-0.988 (0.470)	-0.969 (0.469)	-0.878 (0.468)	-0.933 (0.468)	-3.120 (2.586)
Nonbinary \times Republican Vote Share ²	0.884 (0.456)	0.854 (0.454)	0.766 (0.454)	0.816 (0.453)	2.707 (2.514)
Binary Pronouns	0.034 (0.180)	0.065 (0.184)	0.097 (0.186)	0.074 (0.184)	0.364 (0.387)
Binary \times Republican Vote Share	-0.158 (0.714)	-0.305 (0.714)	-0.424 (0.711)	-0.349 (0.711)	-1.741 (3.631)
Binary \times Republican Vote Share ²	0.085 (0.690)	0.257 (0.691)	0.366 (0.686)	0.306 (0.687)	1.053 (3.576)
Observations	7970	7970	7970	7970	1284
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects are derived from the logistic regression described in equation (4.1). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Vote share is Republican vote share. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 37: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions

	(A)	(B)	(C)	(D)	(E)
Nonbinary Pronouns	-0.020 (0.026)	-0.019 (0.026)	-0.020 (0.026)	-0.019 (0.026)	-0.167 (0.143)
Nonbinary \times Implied Male	0.005 (0.017)	0.005 (0.017)	0.007 (0.016)	0.006 (0.016)	0.043 (0.088)
Nonbinary \times Republican	-0.032 (0.016)	-0.033 (0.016)	-0.034 (0.016)	-0.034 (0.016)	-0.115 (0.091)
Nonbinary \times High Customer-Facing	-0.026 (0.023)	-0.025 (0.023)	-0.028 (0.023)	-0.027 (0.023)	-0.207 (0.117)
Nonbinary \times Low Customer-Facing	-0.036 (0.019)	-0.037 (0.019)	-0.040 (0.019)	-0.039 (0.019)	-0.234 (0.103)
Nonbinary \times Male-Dominated	-0.007 (0.023)	-0.008 (0.023)	-0.003 (0.023)	-0.006 (0.023)	0.040 (0.121)
Nonbinary \times Female-Dominated	0.026 (0.022)	0.019 (0.021)	0.023 (0.021)	0.021 (0.021)	0.179 (0.094)
Nonbinary \times Relevant Experience	-0.002 (0.007)	-0.002 (0.007)	-0.003 (0.007)	-0.003 (0.007)	-0.020 (0.039)
Nonbinary \times Equal Opportunity	0.012 (0.026)	0.020 (0.026)	0.017 (0.026)	0.021 (0.026)	-0.084 (0.146)
Nonbinary \times Gender Sexuality	0.019 (0.033)	0.012 (0.033)	0.016 (0.033)	0.013 (0.033)	0.136 (0.166)
Nonbinary \times Small Business	-0.044 (0.027)	-0.045 (0.027)	-0.040 (0.027)	-0.041 (0.027)	0.046 (0.132)
Binary Pronouns	-0.048 (0.036)	-0.047 (0.036)	-0.047 (0.035)	-0.047 (0.036)	-0.275 (0.171)
Binary \times Implied Male	0.004 (0.025)	0.002 (0.025)	0.001 (0.024)	0.000 (0.024)	-0.015 (0.140)
Binary \times Republican	-0.027 (0.024)	-0.024 (0.024)	-0.023 (0.024)	-0.021 (0.024)	-0.150 (0.125)
Binary \times High Customer-Facing	0.008 (0.036)	0.015 (0.036)	0.014 (0.036)	0.017 (0.036)	0.332 (0.128)
Binary \times Low Customer-Facing	0.000 (0.030)	0.001 (0.030)	0.004 (0.030)	0.004 (0.030)	0.026 (0.167)
Binary \times Male-Dominated	0.044 (0.035)	0.043 (0.035)	0.040 (0.035)	0.038 (0.035)	0.123 (0.178)
Binary \times Female-Dominated	0.025 (0.032)	0.028 (0.033)	0.026 (0.032)	0.024 (0.032)	0.026 (0.171)
Binary \times Relevant Experience	0.009 (0.011)	0.008 (0.011)	0.011 (0.011)	0.010 (0.011)	0.106 (0.060)
Binary \times Equal Opportunity	-0.061 (0.036)	-0.066 (0.037)	-0.069 (0.036)	-0.067 (0.036)	-0.160 (0.227)
Binary \times Gender Sexuality	0.057 (0.052)	0.060 (0.052)	0.060 (0.051)	0.059 (0.051)	0.246 (0.262)
Binary \times Small Business	0.091 (0.045)	0.091 (0.045)	0.079 (0.044)	0.080 (0.044)	-0.061 (0.203)
Observations	7970	7970	7970	7970	1284
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects derived from the logistic regression described in equation (5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 38: Heteroskedastic Logistic Discrimination Estimates (Neu-
mark’s Bias Correction)

	Nonbinary Pronouns	Binary Pronouns
<i>Panel A: Logistic coefficient estimates</i>		
Coefficient Estimate	-0.052 (0.008)	-0.021 (0.013)
<i>Panel B: Heteroskedastic logistic coefficient estimates</i>		
Total Estimate	-0.055 (0.009)	-0.020 (0.014)
Levels Estimate	-0.047 (0.017)	-0.036 (0.030)
Variance Estimate	-0.008 (0.016)	0.016 (0.027)
<i>Panel C: Tests</i>		
Overidentification test p-value (X_i coefficient ratios are equal for treatment and control)	0.928	0.489
Standard deviation of unobservables (treatment / control)	0.952	1.101
Test p-value (ratio of standard deviations = 1)	0.676	0.590
Observations	7970	7970
Resume Controls	X	X
Firm Controls		
Job Posting FE		

Note: This table reports marginal effects for the average applicant 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. Marginal effects are derived from the logistic and heteroskedastic logistic regressions described in equation (1) with resume controls. 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.

Table 39: Estimates of Discrimination Against Male and Female Applicants

	(A)	(B)	(C)	(D)
Implied Male	-0.039 (0.016)	-0.043 (0.022)	-0.046 (0.021)	-0.045 (0.022)
Implied Male \times Female-Dominated	-0.001 (0.020)	-0.003 (0.032)	-0.003 (0.032)	0.002 (0.032)
Implied Female \times Male-Dominated	-0.093 (0.018)	-0.104 (0.026)	-0.105 (0.026)	-0.104 (0.026)
Nonbinary Pronouns	-0.051 (0.008)	-0.053 (0.008)	-0.054 (0.008)	-0.053 (0.008)
Binary Pronouns	-0.022 (0.012)	-0.021 (0.012)	-0.020 (0.012)	-0.020 (0.012)
Observations	7970	7970	7970	7970
Resume Controls		X		X
Firm Controls			X	X
Job Posting FE				

Note: This table reports marginal effects for the average applicant associated with having a name that is implied male versus female. Marginal effects for Panels A to C are derived from the logistic regression described in equation (6). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

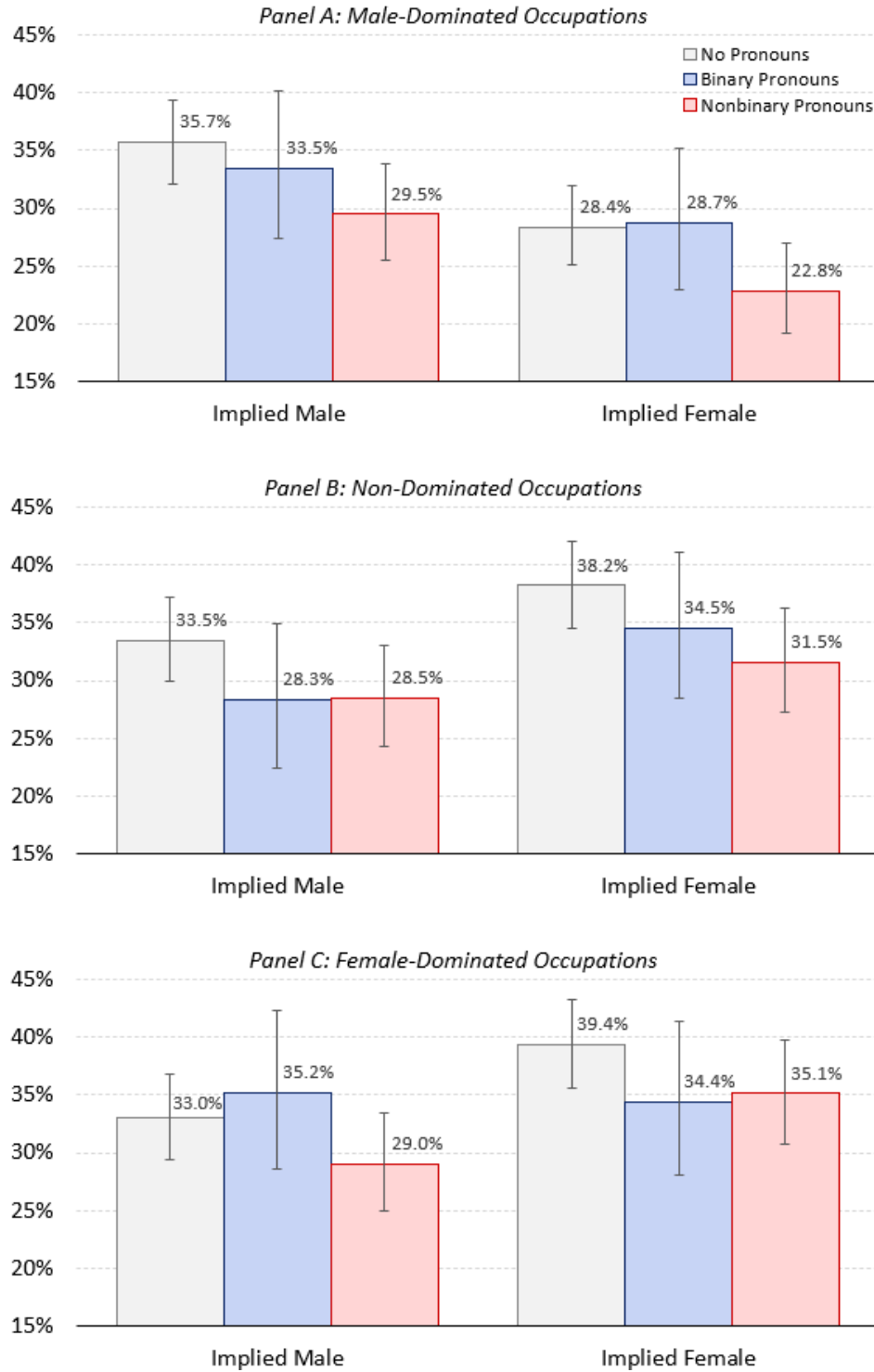


Figure 6: Positive Employer Response Rates by Implied Sex and Pronouns Disclosed

Table 40: Implied Average Discrimination Associated With Nonbinary Pronoun Disclosure by Geographic Republican Vote Share

Vote Share	Implied Discrimination by Regression Specification			
	(A)	(B)	(C)	(D)
30%	-1.7%	-1.6%	-1.8%	-1.6%
35%	-3.8%	-3.6%	-3.7%	-3.6%
40%	-5.4%	-5.3%	-5.2%	-5.2%
45%	-6.6%	-6.5%	-6.3%	-6.4%
50%	-7.3%	-7.3%	-7.1%	-7.2%
55%	-7.6%	-7.6%	-7.4%	-7.6%
60%	-7.5%	-7.6%	-7.4%	-7.5%
65%	-6.9%	-7.1%	-7.0%	-7.1%
70%	-5.8%	-6.2%	-6.3%	-6.3%
Observations	7970	7970	7970	7970
Resume Controls		X		X
Firm Controls			X	X
Job Posting FE				

Note: This table reports implied discrimination associated with disclosing nonbinary “they/them” pronouns compared to not disclosing pronouns, based on geographic (CBSA level) Republican vote share. Implied discrimination is calculated from coefficient estimates reported in Panel B of Table 36.

Table 41: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Experience

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include applicants with relevant experience only</i>					
Nonbinary Pronouns	-0.053 (0.011)	-0.054 (0.012)	-0.055 (0.011)	-0.055 (0.012)	-0.291 (0.055)
Binary Pronouns	-0.030 (0.016)	-0.028 (0.016)	-0.027 (0.016)	-0.026 (0.016)	-0.081 (0.081)
Observations	4610	4610	4610	4610	820
<i>Panel B: Regressions include applicants with no relevant experience only</i>					
Nonbinary Pronouns	-0.051 (0.012)	-0.053 (0.012)	-0.052 (0.011)	-0.052 (0.012)	-0.358 (0.072)
Binary Pronouns	-0.012 (0.017)	-0.009 (0.017)	-0.012 (0.017)	-0.012 (0.017)	-0.093 (0.120)
Observations	3360	3360	3360	3360	464
<i>Panel C: Regressions include all applicants (no squared term)</i>					
Nonbinary Pronouns	-0.049 (0.011)	-0.051 (0.011)	-0.050 (0.011)	-0.049 (0.011)	-0.298 (0.062)
Nonbinary-Years Relevant	-0.003 (0.007)	-0.002 (0.007)	-0.004 (0.007)	-0.003 (0.007)	-0.017 (0.039)
Binary Pronouns	-0.032 (0.017)	-0.028 (0.017)	-0.031 (0.017)	-0.030 (0.017)	-0.214 (0.092)
Binary-Years Relevant	0.009 (0.011)	0.007 (0.011)	0.010 (0.011)	0.009 (0.011)	0.098 (0.060)
Observations	7970	7970	7970	7970	1284
<i>Panel D: Regressions include all applicants (with a squared term)</i>					
Nonbinary Pronouns	-0.039 (0.013)	-0.057 (0.012)	-0.056 (0.012)	-0.056 (0.012)	-0.346 (0.065)
Nonbinary-Years Relevant	0.022 (0.020)	0.022 (0.020)	0.020 (0.020)	0.020 (0.020)	0.181 (0.105)
Nonbinary-Years Relevant ²	-0.008 (0.006)	-0.008 (0.006)	-0.008 (0.006)	-0.008 (0.006)	-0.067 (0.033)
Binary Pronouns	-0.018 (0.019)	-0.015 (0.018)	-0.018 (0.018)	-0.017 (0.018)	-0.120 (0.107)
Binary-Years Relevant	-0.041 (0.030)	-0.040 (0.029)	-0.037 (0.029)	-0.037 (0.029)	-0.224 (0.179)
Binary-Years Relevant ²	0.017 (0.009)	0.016 (0.009)	0.016 (0.009)	0.016 (0.009)	0.113 (0.062)
Observations	7970	7970	7970	7970	1284
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A and B are derived from the logistic regression described in equation (1) with different data subsets; for Panels C and D from (4.2). 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.

Table 42: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Implied Sex

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include implied male applicants only</i>					
Nonbinary Pronouns	-0.050 (0.011)	-0.050 (0.011)	-0.049 (0.011)	-0.050 (0.011)	-0.301 (0.061)
Binary Pronouns	-0.018 (0.017)	-0.020 (0.017)	-0.020 (0.017)	-0.021 (0.017)	-0.145 (0.096)
Observations	3984	3984	3984	3984	626
<i>Panel B: Regressions include implied female applicants only</i>					
Nonbinary Pronouns	-0.054 (0.012)	-0.055 (0.012)	-0.058 (0.011)	-0.056 (0.012)	-0.325 (0.063)
Binary Pronouns	-0.026 (0.017)	-0.022 (0.017)	-0.019 (0.017)	-0.021 (0.017)	-0.092 (0.086)
Observations	3986	3986	3986	3986	658
<i>Panel C: Regressions include all applications</i>					
Nonbinary Pronouns	-0.054 (0.011)	-0.055 (0.011)	-0.057 (0.011)	-0.056 (0.011)	-0.339 (0.059)
Nonbinary \times Implied Male	0.003 (0.017)	0.005 (0.017)	0.007 (0.017)	0.006 (0.016)	0.049 (0.088)
Binary Pronouns	-0.026 (0.017)	-0.021 (0.017)	-0.021 (0.017)	-0.020 (0.017)	-0.078 (0.089)
Binary \times Implied Male	0.008 (0.025)	0.003 (0.024)	0.002 (0.024)	0.001 (0.024)	-0.049 (0.132)
Observations	7970	7970	7970	7970	1284
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A and B are derived from the logistic regression described in equation (1) with different data subsets; for Panel C from (4.3). 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.

Table 43: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Worker Composition (Indicator)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include applications to male-dominated occupations only</i>					
Nonbinary Pronouns	-0.058 (0.014)	-0.062 (0.014)	-0.058 (0.013)	-0.061 (0.014)	-0.357 (0.078)
Binary Pronouns	-0.009 (0.020)	-0.007 (0.020)	-0.011 (0.019)	-0.010 (0.019)	-0.091 (0.119)
Observations	2752	2752	2752	2752	410
<i>Panel B: Regressions include applications to non-dominated occupations only</i>					
Nonbinary Pronouns	-0.057 (0.015)	-0.057 (0.015)	-0.060 (0.014)	-0.060 (0.015)	-0.386 (0.080)
Binary Pronouns	-0.042 (0.020)	-0.040 (0.021)	-0.038 (0.020)	-0.036 (0.021)	-0.027 (0.114)
Observations	2610	2610	2610	2610	452
<i>Panel C: Regressions include applications to female-dominated occupations only</i>					
Nonbinary Pronouns	-0.041 (0.014)	-0.043 (0.014)	-0.043 (0.013)	-0.043 (0.014)	-0.260 (0.076)
Binary Pronouns	-0.014 (0.022)	-0.018 (0.022)	-0.010 (0.022)	-0.018 (0.022)	-0.116 (0.104)
Observations	2608	2608	2608	2608	422
<i>Panel D: Regressions include all applications</i>					
Nonbinary Pronouns	-0.057 (0.014)	-0.054 (0.014)	-0.058 (0.014)	-0.056 (0.014)	-0.378 (0.066)
Nonbinary \times Male-Dominated	-0.004 (0.021)	-0.008 (0.020)	-0.001 (0.020)	-0.005 (0.020)	0.062 (0.107)
Nonbinary \times Female-Dominated	0.018 (0.021)	0.013 (0.020)	0.016 (0.021)	0.015 (0.020)	0.156 (0.098)
Binary Pronouns	-0.042 (0.020)	-0.039 (0.020)	-0.038 (0.020)	-0.036 (0.020)	-0.045 (0.119)
Binary \times Male-Dominated	0.0332 (0.0306)	0.0339 (0.0303)	0.0277 (0.0299)	0.0288 (0.0299)	-0.0931 (0.167)
Binary \times Female-Dominated	0.030 (0.031)	0.028 (0.032)	0.030 (0.032)	0.024 (0.031)	-0.069 (0.156)
Observations	7970	7970	7970	7970	1286
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A to C are derived from the logistic regression described in equation (1) with different data subsets; for Panel D from (4.4). 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.

Table 44: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Worker Composition (Continuous)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regression does not include a squared percent male term</i>					
Nonbinary Pronouns	-0.042 (0.015)	-0.043 (0.015)	-0.047 (0.015)	-0.043 (0.015)	-0.257 (0.087)
Nonbinary \times Percent Male	-0.0207 (0.0254)	-0.0190 (0.0257)	-0.0134 (0.0260)	-0.0185 (0.0258)	-0.1224 (0.1463)
Binary Pronouns	-0.018 (0.023)	-0.019 (0.024)	-0.012 (0.024)	-0.017 (0.024)	-0.099 (0.116)
Binary \times Percent Male	-0.007 (0.038)	-0.002 (0.039)	-0.015 (0.039)	-0.004 (0.038)	-0.002 (0.202)
Observations	7970	7970	7970	7970	1284
<i>Panel B: Regression does include a squared percent male term</i>					
Nonbinary Pronouns	-0.039 (0.021)	-0.042 (0.022)	-0.043 (0.022)	-0.040 (0.022)	-0.225 (0.124)
Nonbinary \times Percent Male	-0.045 (0.110)	-0.029 (0.112)	-0.042 (0.112)	-0.041 (0.112)	-0.331 (0.595)
Nonbinary \times Percent Male ²	0.024 (0.107)	0.010 (0.108)	0.028 (0.108)	0.022 (0.108)	0.209 (0.582)
Binary Pronouns	0.004 (0.033)	0.001 (0.034)	0.007 (0.035)	-0.002 (0.034)	-0.127 (0.163)
Binary \times Percent Male	-0.156 (0.160)	-0.132 (0.163)	-0.138 (0.163)	-0.105 (0.162)	0.200 (0.894)
Binary \times Percent Male ²	0.1483 (0.1549)	0.1286 (0.1557)	0.1215 (0.1561)	0.0999 (0.1552)	-0.2045 (0.885)
Observations	7970	7970	7970	7970	1284
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects derived from the logistic regression described in equation (4.4). 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.

Table 45: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Customer Interaction (Indicator)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include applications to high customer-facing occupations only</i>					
Nonbinary Pronouns	-0.052 (0.015)	-0.053 (0.016)	-0.056 (0.015)	-0.055 (0.016)	-0.359 (0.083)
Binary Pronouns	-0.027 (0.022)	-0.026 (0.022)	-0.019 (0.022)	-0.022 (0.022)	0.068 (0.122)
Observations	2352	2352	2352	2352	410
<i>Panel B: Regressions include applications to medium customer-facing occupations only</i>					
Nonbinary Pronouns	-0.034 (0.015)	-0.032 (0.015)	-0.033 (0.014)	-0.031 (0.015)	-0.169 (0.089)
Binary Pronouns	-0.019 (0.021)	-0.020 (0.022)	-0.023 (0.021)	-0.023 (0.021)	-0.204 (0.117)
Observations	2372	2372	2372	2372	362
<i>Panel C: Regressions include applications to low customer-facing occupations only</i>					
Nonbinary Pronouns	-0.066 (0.013)	-0.065 (0.013)	-0.068 (0.012)	-0.065 (0.013)	-0.358 (0.069)
Binary Pronouns	-0.020 (0.019)	-0.019 (0.019)	-0.016 (0.019)	-0.017 (0.018)	-0.130 (0.098)
Observations	3246	3246	3246	3246	512
<i>Panel D: Regressions include all applications</i>					
Nonbinary Pronouns	-0.035 (0.015)	-0.035 (0.015)	-0.033 (0.015)	-0.034 (0.015)	-0.168 (0.088)
Nonbinary \times High Customer-Facing	-0.018 (0.021)	-0.017 (0.021)	-0.023 (0.021)	-0.019 (0.021)	-0.192 (0.111)
Nonbinary \times Low Customer-Facing	-0.029 (0.019)	-0.031 (0.019)	-0.035 (0.019)	-0.032 (0.019)	-0.211 (0.105)
Binary Pronouns	-0.020 (0.022)	-0.019 (0.021)	-0.023 (0.021)	-0.022 (0.021)	-0.195 (0.107)
Binary \times High Customer-Facing	-0.008 (0.032)	-0.003 (0.032)	0.002 (0.032)	0.002 (0.032)	0.294 (0.125)
Binary \times Low Customer-Facing	0.000 (0.029)	0.001 (0.029)	0.007 (0.029)	0.004 (0.029)	0.029 (0.156)
Observations	7970	7970	7970	7970	1284
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A to C are derived from the logistic regression described in equation (1) with different data subsets; for Panel D from (4.5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 46: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Customer Interaction (Continuous)

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regression does not include a squared O*NET customer interaction score term</i>					
Nonbinary Pronouns	-0.062 (0.025)	-0.065 (0.024)	-0.063 (0.024)	-0.064 (0.024)	-0.322 (0.115)
Nonbinary \times O*NET Score	0.0002 (0.0004)	0.0002 (0.0004)	0.0002 (0.0004)	0.0002 (0.0004)	0.0001 (0.0021)
Binary Pronouns	-0.024 (0.035)	-0.024 (0.035)	-0.025 (0.034)	-0.024 (0.034)	-0.388 (0.125)
Binary \times O*NET Score	0.0000 (0.0006)	0.0001 (0.0006)	0.0001 (0.0006)	0.0001 (0.0006)	0.0064 (0.0034)
Observations	7970	7970	7970	7970	1284
<i>Panel B: Regression does include a squared O*NET customer interaction score term</i>					
Nonbinary Pronouns	-0.101 (0.066)	-0.100 (0.069)	-0.106 (0.068)	-0.102 (0.068)	-0.566 (0.093)
Nonbinary \times O*NET Score	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.018 (0.013)
Nonbinary \times O*NET Score ²	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0001 (0.0001)
Binary Pronouns	-0.109 (0.074)	-0.091 (0.081)	-0.100 (0.078)	-0.087 (0.081)	0.137 (0.536)
Binary \times O*NET Score	0.0035 (0.0031)	0.0027 (0.0032)	0.0031 (0.0031)	0.0025 (0.0032)	-0.0150 (0.0196)
Binary \times O*NET Score ²	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	0.0002 (0.0002)
Observations	7970	7970	7970	7970	1284
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects are derived from the logistic regression described in equation (4.5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 47: Estimates of Discrimination Against Applicants who Disclose Pronouns: by Job Posting Text

	(A)	(B)	(C)	(D)	(E)
<i>Panel A: Regressions include applications to job postings mentioning “equal opportunity”</i>					
Nonbinary Pronouns	-0.035 (0.017)	-0.039 (0.018)	-0.035 (0.017)	-0.036 (0.018)	-0.362 (0.096)
Binary Pronouns	-0.051 (0.026)	-0.050 (0.027)	-0.053 (0.026)	-0.054 (0.027)	-0.066 (0.172)
Observations	1644	1644	1644	1644	244
<i>Panel B: Regressions include applications to job postings mentioning gender or sexuality</i>					
Nonbinary Pronouns	-0.030 (0.023)	-0.034 (0.024)	-0.034 (0.022)	-0.033 (0.024)	-0.314 (0.117)
Binary Pronouns	-0.013 (0.033)	-0.008 (0.034)	-0.006 (0.032)	-0.013 (0.033)	0.203 (0.174)
Observations	962	962	962	962	132
<i>Panel C: Regressions include applications to job postings mentioning small business</i>					
Nonbinary Pronouns	-0.092 (0.028)	-0.096 (0.029)	-0.085 (0.027)	-0.088 (0.029)	-0.285 (0.140)
Binary Pronouns	0.052 (0.041)	0.054 (0.041)	0.037 (0.039)	0.039 (0.039)	0.132 (0.166)
Observations	798	798	798	798	152
<i>Panel D: Regressions include applications to job postings mentioning none of the above</i>					
Nonbinary Pronouns	-0.053 (0.010)	-0.054 (0.010)	-0.055 (0.009)	-0.054 (0.010)	-0.332 (0.055)
Binary Pronouns	-0.019 (0.014)	-0.017 (0.014)	-0.015 (0.014)	-0.016 (0.014)	-0.084 (0.078)
Observations	5596	5596	5596	5596	872
<i>Panel E: Regressions All Applications</i>					
Nonbinary Pronouns	-0.053 (0.010)	-0.054 (0.010)	-0.055 (0.009)	-0.054 (0.010)	-0.324 (0.052)
Nonbinary \times Equal Opportunity	0.015 (0.026)	0.020 (0.026)	0.019 (0.026)	0.020 (0.026)	-0.074 (0.147)
Nonbinary \times Gender or Sexuality	0.012 (0.033)	0.012 (0.033)	0.011 (0.033)	0.012 (0.033)	0.130 (0.169)
Nonbinary \times Small Business	-0.040 (0.028)	-0.044 (0.027)	-0.037 (0.027)	-0.040 (0.027)	0.060 (0.134)
Binary Pronouns	-0.024 (0.014)	-0.022 (0.014)	-0.020 (0.014)	-0.020 (0.014)	-0.087 (0.077)
Binary \times Equal Opportunity	-0.066 (0.037)	-0.064 (0.036)	-0.072 (0.035)	-0.065 (0.036)	-0.197 (0.221)
Binary \times Gender or Sexuality	0.067 (0.051)	0.059 (0.051)	0.069 (0.051)	0.058 (0.051)	0.304 (0.223)
Binary \times Small Business	0.080 (0.044)	0.090 (0.045)	0.074 (0.043)	0.078 (0.044)	-0.062 (0.199)
Observations	7970	7970	7970	7970	1284
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects for Panels A to D are derived from the logistic regression described in equation (1) with different data subsets; for Panel E from (4.6). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 48: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions (Continuous, No Squares)

	(A)	(B)	(C)	(D)	(E)
Nonbinary Pronouns	-0.006 (0.045)	-0.012 (0.044)	-0.010 (0.044)	-0.010 (0.044)	-0.069 (0.255)
Nonbinary \times Implied Male	0.005 (0.017)	0.005 (0.017)	0.007 (0.017)	0.006 (0.016)	0.045 (0.089)
Nonbinary \times Vote Share	-0.086 (0.063)	-0.090 (0.059)	-0.093 (0.059)	-0.093 (0.059)	-0.347 (0.342)
Nonbinary \times O*NET Score	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.002)
Nonbinary \times Percent Male	-0.024 (0.026)	-0.017 (0.026)	-0.015 (0.027)	-0.016 (0.026)	-0.129 (0.151)
Nonbinary \times Relevant Experience	-0.003 (0.007)	-0.002 (0.007)	-0.004 (0.007)	-0.003 (0.007)	-0.014 (0.038)
Nonbinary \times Equal Opportunity	0.013 (0.026)	0.019 (0.026)	0.016 (0.026)	0.020 (0.026)	-0.078 (0.146)
Nonbinary \times Gender Sexuality	0.016 (0.033)	0.010 (0.033)	0.014 (0.033)	0.010 (0.033)	0.119 (0.168)
Nonbinary \times Small Business	-0.042 (0.027)	-0.044 (0.027)	-0.039 (0.027)	-0.041 (0.027)	0.055 (0.133)
Binary Pronouns	-0.003 (0.069)	-0.011 (0.066)	-0.006 (0.066)	-0.012 (0.066)	-0.313 (0.293)
Binary \times Implied Male	0.006 (0.025)	0.003 (0.025)	0.001 (0.024)	0.001 (0.024)	-0.018 (0.145)
Binary \times Vote Share	-0.079 (0.095)	-0.052 (0.092)	-0.052 (0.091)	-0.047 (0.092)	-0.548 (0.490)
Binary \times O*NET Score	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.007 (0.004)
Binary \times Percent Male	0.007 (0.040)	0.002 (0.040)	-0.001 (0.041)	0.001 (0.040)	0.074 (0.213)
Binary \times Relevant Experience	0.009 (0.011)	0.008 (0.011)	0.011 (0.011)	0.010 (0.011)	0.098 (0.061)
Binary \times Equal Opportunity	-0.061 (0.036)	-0.064 (0.037)	-0.068 (0.036)	-0.066 (0.036)	-0.202 (0.215)
Binary \times Gender Sexuality	0.055 (0.052)	0.057 (0.052)	0.057 (0.051)	0.056 (0.051)	0.279 (0.241)
Binary \times Small Business	0.087 (0.045)	0.090 (0.045)	0.078 (0.044)	0.079 (0.044)	-0.106 (0.196)
Observations	7970	7970	7970	7970	1284
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects derived from the logistic regression described in equation (5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.

Table 49: Estimates of Discrimination Against Applicants who Disclose Pronouns: All Interactions (Continuous, Including Squares)

	(A)	(B)	(C)	(D)	(E)
Nonbinary Pronouns	0.165 (0.134)	0.153 (0.138)	0.133 (0.139)	0.143 (0.138)	0.042 (0.723)
Nonbinary \times Implied Male	0.004 (0.017)	0.005 (0.017)	0.007 (0.017)	0.006 (0.016)	0.046 (0.087)
Nonbinary \times Vote Share	-1.023 (0.467)	-0.969 (0.468)	-0.921 (0.467)	-0.929 (0.467)	-3.173 (2.579)
Nonbinary \times Vote Share ²	0.913 (0.453)	0.857 (0.453)	0.806 (0.452)	0.815 (0.452)	2.753 (2.508)
Nonbinary \times O*NET Score	0.002 (0.002)	0.001 (0.003)	0.002 (0.003)	0.002 (0.003)	0.018 (0.013)
Nonbinary \times O*NET Score ²	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Nonbinary \times Percent Male	-0.023 (0.118)	-0.016 (0.124)	-0.028 (0.123)	-0.027 (0.123)	-0.067 (0.633)
Nonbinary \times Percent Male ²	0.004 (0.117)	0.001 (0.121)	0.016 (0.120)	0.013 (0.120)	-0.036 (0.625)
Nonbinary \times Relevant Experience	0.025 (0.020)	0.023 (0.020)	0.021 (0.020)	0.021 (0.020)	0.179 (0.106)
Nonbinary \times Relevant Experience ²	-0.009 (0.006)	-0.008 (0.006)	-0.008 (0.006)	-0.008 (0.006)	-0.063 (0.033)
Nonbinary \times Equal Opportunity	0.012 (0.026)	0.019 (0.026)	0.016 (0.026)	0.020 (0.026)	-0.071 (0.144)
Nonbinary \times Gender Sexuality	0.016 (0.033)	0.011 (0.033)	0.015 (0.033)	0.012 (0.033)	0.120 (0.170)
Nonbinary \times Small Business	-0.045 (0.027)	-0.046 (0.027)	-0.040 (0.027)	-0.042 (0.027)	0.016 (0.138)
Binary Pronouns	-0.023 (0.206)	0.036 (0.223)	0.036 (0.220)	0.042 (0.222)	0.422 (0.290)
Binary \times Implied Male	0.007 (0.025)	0.003 (0.025)	0.001 (0.024)	0.001 (0.024)	-0.020 (0.145)
Binary \times Vote Share	-0.209 (0.715)	-0.421 (0.722)	-0.453 (0.715)	-0.465 (0.719)	-1.661 (3.682)
Binary \times Vote Share ²	0.139 (0.692)	0.357 (0.697)	0.390 (0.690)	0.406 (0.694)	1.034 (3.646)
Binary \times O*NET Score	0.003 (0.003)	0.002 (0.003)	0.003 (0.003)	0.002 (0.003)	-0.012 (0.023)
Binary \times O*NET Score ²	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Binary \times Percent Male	-0.087 (0.174)	-0.072 (0.180)	-0.055 (0.179)	-0.042 (0.179)	-0.620 (1.008)
Binary \times Percent Male ²	0.094 (0.170)	0.079 (0.174)	0.058 (0.173)	0.047 (0.173)	0.738 (0.993)
Binary \times Relevant Experience	-0.046 (0.029)	-0.043 (0.029)	-0.040 (0.029)	-0.040 (0.029)	-0.196 (0.192)
Binary \times Relevant Experience ²	0.019 (0.009)	0.017 (0.009)	0.017 (0.009)	0.017 (0.009)	0.103 (0.067)
Binary \times Equal Opportunity	-0.061 (0.036)	-0.066 (0.037)	-0.069 (0.036)	-0.067 (0.036)	-0.212 (0.207)
Binary \times Gender Sexuality	0.058 (0.052)	0.059 (0.052)	0.060 (0.051)	0.058 (0.051)	0.229 (0.280)
Binary \times Small Business	0.094 (0.045)	0.094 (0.045)	0.081 (0.044)	0.083 (0.044)	-0.066 (0.201)
Observations	7970	7970	7970	7970	1244
Resume Controls		X		X	X
Firm Controls			X	X	X
Job Posting FE					X

Note: This table reports marginal effects for the average applicant 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. Marginal effects derived from the logistic regression described in equation (5). The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses.