How Does Sex-Based Occupational Discrimination Affect Nonbinary Applicants? Evidence from a Correspondence Experiment

By TARYN EAMES*

Women have historically faced myriad disadvantages in the labor market, leading to unequal outcomes. However, recent decades have seen a reduction in such inequality (Goldin 2014). In the case of hiring discrimination, recent research suggests that, rather than always disadvantaging women, the direction of sex-based discrimination is now based on occupation-specific factors. In particular, while women face discrimination in male-dominated occupations, the opposite is true for men (e.g., Yavorsky 2019).

Existing research predominantly focuses on cisgender individuals. Yet, an increasing number of people identify as a gender different from their sex assigned at birth, with nonbinary identities (outside the male-female binary) being the most common (Brown 2022). Further, this group experiences worse labor market outcomes (e.g., Carpenter et al. 2024) and faces discrimination both in the labor market (Eames 2024) and other areas (Fumarco et al. 2024).

This paper contributes to the literature by examining how the intersection of sex and nonbinary gender identity affects hiring discrimination. First, I ask: do male and female nonbinary applicants face different levels of discrimination? This question is motivated by evidence that, within the LGBT community, people assigned male at birth tend to fare worse in the labor market. This includes same-sex wage gaps (e.g., Drydakis 2021), hiring discrimination (e.g., Flage 2020), and post-transition earnings reductions for transgender men and women (e.g., Carpenter, Goodman and Lee 2024).

Overall differences may mask occupation-specific heterogeneity. Thus, I also ask: do patterns of sex-based discrimination differ between presumably cisgender applicants and those who disclose "they/them" pronouns? The answer is ex-ante ambiguous: such disclosure may influence perceptions of an applicant's proximity to male-ness or female-ness. For instance, nonbinary pronouns disclosed by male-named applicants might lead employers to perceive them as "more female," either due to uncertainty about their sex or assumptions of femininity. This could mitigate sex-based discrimination in female-dominated occupations and vice versa.

I find no difference in employer response between male and female nonbinary applicants. Given occupational sex composition, I find that nonbinary applicants face discrimination patterns resembling cisgender applicants with the same name-implied sex. I also find evidence of double discrimination: applicants who are both the non-dominant sex and also disclose "they/them" pronouns are doubly penalized.

I. Data

This study uses data from Eames (2024), a correspondence experiment on hiring discrimination against nonbinary applicants where identity is signaled by listing "they/them" pronouns on their resume. Resumes were submitted to job postings across 15 occupations, which vary in

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sex composition and are described in Table 1.

Table 1—: Occupations

Occupation	% Male	Category	N
Admin Assistant (AA)	6	F Dominated	365
Receptionist (R)	9	F Dominated	500
Nursing Assistant (N)	11	F Dominated	642
Housekeeper (H)	15	F Dominated	380
Cashier (Ca)	28	F Dominated	316
Server (S)	36	Mixed	332
Baker (B)	44	Mixed	159
Cook (Ck)	59	Mixed	573
Retail Salesperson (RS)	62	Mixed	834
Assembler (A)	62	Mixed	271
Janitor (J)	70	M Dominated	379
Warehouse Worker (W)	80	M Dominated	552
Landscaper (L)	94	M Dominated	358
Truck Driver (T)	95	M Dominated	663
Construction Worker (C)	97	M Dominated	356

Worker sex composition data is from the 2019 American Community Survey. Occupation categories were pre-specified—"F Dominated" is female-dominated; "M Dominated" is male-dominated.

Resumes were submitted in pairs to U.S. job postings; in each pair, one resume listed pronouns below the applicant's name and the other did not. Paired resumes were randomly generated and matched on key attributes to ensure applicants had the same implied sex (signaled via first name) and were of similar quality. Eames (2024) includes full experimental details.

II. Empirical Strategy

To estimate whether nonbinary applicants with male-sounding or female-sounding names experience different rates of discrimination, I run the following linear probability model:

$$(1)\quad y_{iocj} = \lambda F_i + \gamma_1 NB_i + \gamma_2[F_i \cdot NB_i] + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj}$$

where y_{ipj} equals one when applicant i in occupation o and city c receives a positive response from job posting j, NB_i equals one if the applicant lists "they/them" pronouns on their resume,F_i equals one if the applicant is implied female (through name), X_i and Z_j are vectors of resume and job posting characteristics that may influence baseline employer response (see the Online Appendix), η_o are occupation fixed effects, δ_c are city fixed effects, and ε_{iocj} is an error term.

To estimate sex-based discrimination, I run the following linear probability model. This regression is run separately for applicants who do not disclose any pronouns and for applicants who disclose nonbinary "they/them" pronouns, to allow for distinct group-specific patterns:

$$(2)\quad y_{iocj} = \lambda_1 F_i + \lambda_2[F_i \cdot MD_j] + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj}$$

where MD_j equals one if an occupation is male-dominated.[1]

Equations (1) and (2) assume that sex-based discrimination follows a step-function pattern, meaning discrimination occurs only after the sex composition crosses a specific threshold. To investigate this, I also semi-parametrically investigate the relationship between positive employer response and occupation sex composition using a two-step approach. First, I estimate the following linear probability model that controls for resume and job posting characteristics but omits the variables of interest:

$$(3)\quad y_{iocj} = X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj}$$

From (3) I compute residuals $(y_{iocj} - \hat{y}_{iocj})$, representing the portion of employer response unexplained by baseline characteristics, ignoring applicant sex and pronoun disclosure.

Second, I apply Nadaraya-Watson kernel smoothing to estimate average residuals as a function of occupation sex composition (percent of workers male). This is done separately

[1] In the Online Appendix, an alternative specification $(2)'$ is investigated, where F_i and NB_i are additionally interacted with FD_j (which equals one if an occupation is female-dominated). Results are consistent between (2) and $(2)'$.

for males and females who disclose "they/them" pronouns and who do not disclose any pronouns. Average residuals above zero indicate that, at a given sex composition, the group's employer response rates are being systematically underestimated; below zero indicate overestimation. As such, this kernel estimation flexibly and nonlinearly estimates how occupation sex composition affects employer response, allowing unique patterns for each group.

Finally, to assess whether applicants are doubly penalized when they hold more than one minoritized identity (for example, applicants who are both of the non-dominant sex and also disclose "they/them" pronouns), I run the following linear probability model:

$$y_{iocj} = \theta_1 HO_i + \theta_2 HT_i + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj} \tag{4}$$

where HO_i equals one when an applicant holds one or more minoritized identities (they are either the non-dominant sex or disclose "they/them" pronouns) and HT_i equals one when an applicant holds both minoritized identities.[2] As such, $\hat{\theta}_1$ represents estimated discrimination against applicants who are minoritized either due to their sex or nonbinary gender identity; $\hat{\theta}_2$ represents *additional* discrimination resulting from being minoritized across both dimensions.

III. Results

Table 2 presents the results of equation (1), and shows that both male and female nonbinary applicants face discrimination—I can rule out the possibility that either group avoids hiring discrimination. While precision is limited, the results also suggest minimal differences in the extent of discrimination faced by males and females, with an estimated 0.5 percentage point difference between them.

Table 2—: Sex-Based Differences in Hiring Discrimination Against Nonbinary Applicants

	Coefficient Estimate
Female	0.009 (0.015) [-0.020, 0.038]
"they/them"	-0.052 *** (0.011) [-0.074, -0.031]
"they/them" × Female	-0.005 (0.016) [-0.036, 0.026]
Observations	6,680

Note: This table reports coefficient estimates from equation (1), where the dependent variable equals one if the applicant received a positive employer response. Coefficient estimates for control variables are not shown. Coefficient estimates for control variables are not shown. Standard errors are clustered at the job posting level and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1%, ** 5%, * 10% level.

Table 3 presents the results of equation (2). Consistent with existing research, presumably cisgender applicants with female-sounding names are 5.4 percentage points (18%) more likely than those with male-sounding names to receive positive responses in female-dominated and mixed occupations. This advantage reverses in male-dominated occupations, where they are 7.9 percentage points (24%) less likely to receive positive responses.

These estimates closely align with those for applicants who disclose "they/them" pronouns, particularly when expressed proportionally rather than in percentage points. Compared to applicants with male-sounding names, those with female-sounding names are 4.1 percentage points (17%) more likely to receive positive responses in female-dominated and mixed occupations but 6.9 percentage points (26%) less likely in male-dominated occupations. As such, when it comes to occupational sex composition, nonbinary applicants experience the same direction of discrimination as those who are presumably

[2]Females are the non-dominant sex in male-dominated occupations; males are the non-dominant sex in female-dominanted and mixed occupations.

cisgender, with nearly identical estimated magnitudes.

Table 3—: Patterns in Sex-Based Discrimination

	Coefficient Estimate
Panel A: No pronouns disclosed	
Female	0.054 *** (0.018) [0.018, 0.089]
Female × Male Dominated	-0.133 *** (0.030) [-0.191, -0.074]
Observations	3,985
Panel B: "they/them" pronouns disclosed	
Female	0.041 * (0.021) [0.000, 0.083]
Female × Male Dominated	-0.110 *** (0.035) [-0.178, -0.043]
Observations	2,695

Note: This table reports coefficient estimates from equation (2), where the dependent variable equals one if the applicant received a positive employer response. Coefficient estimates for control variables are not shown. Standard errors are clustered at the job posting level and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1%, ** 5%, * 10% level.

However, these results assume that, when expressed as a function of occupational sex composition, discrimination acts as a step function. This may mask differences in how nonbinary and presumably cisgender applicants experience patterns in discrimination within occupation categories. To consider this, Figure 1 presents group-specific semi-parametric relationships between an occupation's sex composition (percent of workers male) and average residual, estimated via the two-step strategy described above. Consistent with Table 3, these semi-parametric estimates indicate that females have higher positive employer response rates than males in female-dominated and mixed occupations, but this reverses in male-dominated occupations. Notably, residual trends for applicants with both female-sounding and male-sounding names are similar whether or not they disclose nonbinary pronouns. Instead, disclosure appears to impose a consistent penalty across all compositions (i.e., the same male and female curves are shifted down).

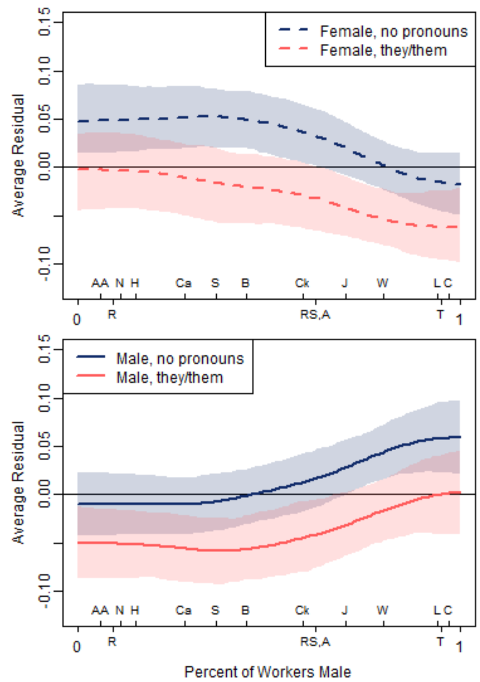

Figure 1. : Average Residuals by Sex and Pronouns

Note: This figure shows group-specific average residuals from equation (2), estimated via kernel smoothing. Occupation sex compositions are indicated along the x-axis; see Table 1 for occupation names. Kernel estimates use a bandwidth of 0.15; alternative bandwidths results are shown in Figure A1 in the Online Appendix, and are consistent with the above. Shaded areas show 95% confidence intervals, bootstrapped with 1,000 resampled datasets. Residuals above (below) zero indicate that predicted positive employer response is systematically underestimated (overestimated).

As such, there appears to be double discrimination: applicants are penalized once for being the non-dominant sex (given an occupation's sex composition) and again for disclosing nonbinary "they/them" pronouns. Applicants who are *both* the non-dominant sex and disclose nonbinary pronouns are penalized twice. This is also shown in Table 4, which presents the results of equation (4). When applicants are minoritized once (via sex or their nonbinary gender identity), they receive a penalty of 6.5 percentage points

(19%). When applicants are minoritized twice, discrimination grows to 11.4 percentage points (33%)—a sizable increase.

Table 4—: Double Discrimination

	Coefficient Estimate
One or More Minoritized Identities	-0.065 *** (0.011) [-0.086, -0.043]
Two Minoritized Identities	-0.049 *** (0.011) [-0.074, -0.028]
Observations	6,680

Note: This table reports coefficient estimates from equation (4), where the dependent variable equals one if the applicant received a positive employer response. Standard errors are clustered at the job posting level and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1%, ** 5%, * 10% level.

IV. Discussion

This study provides the first evidence of how the intersection of sex and nonbinary gender identity influences hiring discrimination, and patterns across occupations with varied sex compositions. I find that male and female nonbinary applicants experience discrimination of a similar magnitude. In addition, applicants who disclose “they/them” pronouns experience trends in hiring discrimination similar to presumably cisgender applicants with the same name-implied sex: those with female-sounding names are discriminated against in male-dominated occupations, and vice versa. Across all occupations, applicants face a consistent penalty associated with disclosing “they/them” pronouns. This penalty appears to be independent of implied sex and additive, leading to double discrimination. This may suggest that disclosing “they/them” pronouns does not strongly alter employer perceptions of proximity to male-ness or female-ness (although this is not the only explanation for the observed discrimination patterns).

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Online Appendix

This Appendix includes:

- **Control Variables:** Tables A1 and A2 contain descriptions of all variables included in the vector of resume controls (X_i) and job posting controls (Z_j) respectively.

- **Alternative Linear Probability Results:** Recall that equation (2) does not include FD_j interactions. An alternative specification is run here, including those interactions:

  $$(2)' \quad y_{iocj} = \lambda_1 F_i + \lambda_2[F_i \cdot FD_j] + \lambda_3[F_i \cdot MD_j] \\ + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj}$$

  Results for are presented in Table A3. For both presumably cisgender and nonbinary people, there is no statistically significant difference in positive employer response in female-dominated and mixed occupations (and point estimates are low). However, considering all three occupation categories reduces power and precision; hence, specification (2) is preferred.

- **Additional Linear Probability Results:** Equations (2) and $(2)'$ show that presumably cisgender and nonbinary applicants experience the same direction of discrimination and that estimated magnitudes are similar. However, they do not formally test whether discrimination magnitude is different for these groups. To address this, I run the following triple-interaction linear probability model including all applicants:

  $$(5) \quad y_{iocj} = \lambda_1 F_i + \lambda_2[F_i \cdot MD_j] + \gamma_1 NB_i + \gamma_2[NB_i \cdot MD_j] \\ + \xi_1[F_i \cdot NB_i] + \xi_2[F_i \cdot NB_i \cdot MD_j] + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj}$$

  $$(5)' \quad y_{iocj} = \lambda_1 F_i + \lambda_2[F_i \cdot PM_j] + \gamma_1 NB_i + \gamma_2[NB_i \cdot PM_j] \\ + \xi_1[F_i \cdot NB_i] + \xi_2[F_i \cdot NB_i \cdot PM_j] + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj}$$

  where in equation $(5)'$ sex composition indicator variables are replaced with PM_j which represents the percent of the occupation's workers who are male. In these regressions, $\hat{\xi}_2$ can be interpreted as the estimated difference in discrimination magnitude between females who are presumably cisgender and those who are nonbinary. Results are shown in Tables A4 and A5. First, the estimated difference in discrimination magnitude is statistically insignificant. Further, by comparing the upper and lower bounds of $\hat{\xi}_2$ to $\hat{\lambda}_2$, I can estimate that sex-based discrimination against nonbinary females in male-dominated occupations ranges from 46% to 120% of the magnitude faced by presumably cisgender females (28% to 136% when consider percent of workers male).

- **Alternative Semi-Parametric Results:** Recall that in the main paper, kernel estimation used a bandwidth of 0.15; Figures A2 and A3 present results using bandwidth levels $0.05, 0.10, 0.15$, and 0.20. Results are consistent across bandwidth levels; as expected, there is more noise when bandwidth is lower.

Tables

Table A1: Resume Characteristics (X_i Control Variables)

Variable	Type	Description
Binary Pronouns	Indicator	Equals 1 if the applicant lists "he/him" or "she/her" pronouns congruent with name-implied sex on his or her resume
Sent first	Indicator	Equals 1 if the resume was sent first
Resume lag	Discrete	Equals 0 if the resume was sent first, and the hours between the first and second application if the resume was sent second
Resume lag^2	Discrete	Above squared
GED	Indicator	Equals 1 if the applicant achieved a GED
Associate's	Indicator	Equals 1 if the applicant achieved an Associate's degree
Bachelor's	Indicator	Equals 1 if the applicant achieved a Bachelor's degree
High Score High School	Indicator	Equals 1 if the applicant went to a high school with test scores rated 'A' by Niche
Low Score High School	Indicator	Equals 1 if the applicant went to a high school with test scores rated 'C' or below by Niche
Worked in HS	Indicator	Equals 1 if the applicant worked during high school
Years relevant	Discrete	Equals the number of years of "relevant" work experience.
Years relevant^2	Discrete	Above squared
Current relevant	Indicator	Equals 1 if the applicant's most recent work experience is "relevant"
Current most common	Indicator	Equals 1 if the applicant's most recent work experience is "most common"
Current common	Indicator	Equals 1 if the applicant's most recent work experience is "common"
Prior most common	Discrete	Equals the years of "most common" experience, omitting most recent experience
Prior most common^2	Discrete	Above squared
Prior common	Discrete	Equals the years of "common" experience, omitting most recent experience
Prior common^2	Discrete	Above squared
Summary	Indicator	Equals 1 if the resume includes a summary or objective section
Skill: communication	Indicator	Equals 1 if the applicant's resume lists "clear communicator" as a skill
Skill: computer	Indicator	Equals 1 if the applicant's resume lists "computer skills (tech savvy)" as a skill
Skill: detail oriented	Indicator	Equals 1 if the applicant's resume lists "detail oriented" as a skill
Skill: fast learner	Indicator	Equals 1 if the applicant's resume lists "fast learner" as a skill
Skill: fast-paced	Indicator	Equals 1 if the applicant's resume lists "thrives in fast-paced settings" as a skill
Skill: leader	Indicator	Equals 1 if the applicant's resume lists "leadership abilities" as a skill
Skill: organized	Indicator	Equals 1 if the applicant's resume lists "organized and efficient" as a skill
Skill: team player	Indicator	Equals 1 if the applicant's resume lists "team player" as a skill
Binary Pronouns	Indicator	Equals 1 if the applicant's resume lists "he/him" or "she/her" pronouns congruent with name-implied sex. This was an additional treatment arm in Eames (2024); this treatment arm is out-of-scope for this paper.

Work experience is considered "relevant" if it is in the position being applied for (e.g., if an applicant is applying to a janitor position, janitorial experience is "relevant"). Work experience is considered "most common" if it is in the position observed to be most common among non-"relevant" past experiences. This position is occupation-specific, and identified from the resume-scraping process described in Section A1.6 in the Online Appendix of Eames (2024): 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 A2: Job Posting Characteristics (Z_j Control Variables)

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

Table A3: Patterns in Sex-Based Discrimination
(Considering Three Occupation Categories)

	Coefficient Estimate
Panel A: No pronouns disclosed	
Female	0.049 * (0.026) [-0.002, 0.100]
Female × Female Dominated	0.009 (0.036) [-0.061, 0.079]
Female × Male Dominated	-0.128 *** (0.035) [-0.197, -0.059]
Observations	3,985
Panel B: "they/them" pronouns disclosed	
Female	0.035 (0.030) [-0.025, 0.094]
Female × Female Dominated	0.012 (0.042) [-0.069, 0.094]
Female × Male Dominated	-0.104 ** (0.041) [-0.184, -0.024]
Observations	2,695

Note: This table reports coefficient estimates from equation (2)′, where the dependent variable equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 1%, ** 5%, * 10% level.

Table A4: Triple-Interaction Discrimination Estimates
(Using Occupation Sex Composition Categories)

	Coefficient Estimate
Female	0.055 *** (0.018) [0.020, 0.090]
Female × Male Dominated	-0.134 (0.030) [-0.192, -0.075]
"they/them"	-0.047 *** (0.013) [-0.073, -0.020]
"they/them" × Male Dominated	-0.016 (0.023) [-0.061, 0.030]
"they/them" × Female	-0.015 (0.020) [-0.054, 0.024]
"they/them" × Female × Male Dominated	0.029 (0.033) [-0.035, 0.093]
Observations	6,680

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

Table A5: Triple-Interaction Discrimination Estimates
(Using Percent of Workers Male)

	Coefficient Estimate
Female	0.100 *** (0.027) [0.046, 0.153]
Female × Percent of Workers Male	-0.172 *** (0.044) [-0.257, -0.086]
"they/them"	-0.039 * (0.020) [-0.078, 0.001]
"they/them" × Percent of Workers Male	-0.025 (0.033) [-0.091, 0.040]
"they/them" × Female	-0.022 (0.030) [-0.080, 0.036]
"they/them" × Female × Percent of Workers Male	0.031 (0.048) [-0.062, 0.124]
Observations	6,680

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

Figures

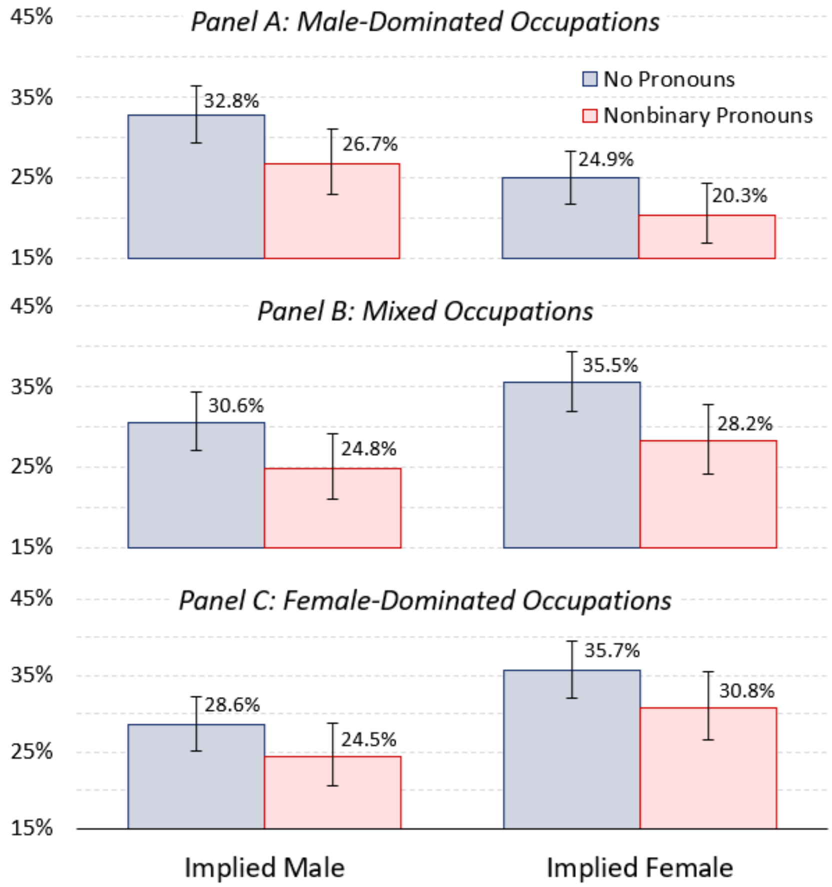

Figure A1: Positive Employer Response Rates
(by Occupation Type, Sex, and Pronoun Disclosure)

Note: This figure reports positive employer response rates for males and females who disclose no pronouns versus nonbinary pronouns, across male-dominated, mixed, and female-dominated occupation types. Whiskers show the 95% confidence interval associated with the true positive employer response rate for each group, calculated using the normal approximation to the binomial distribution.

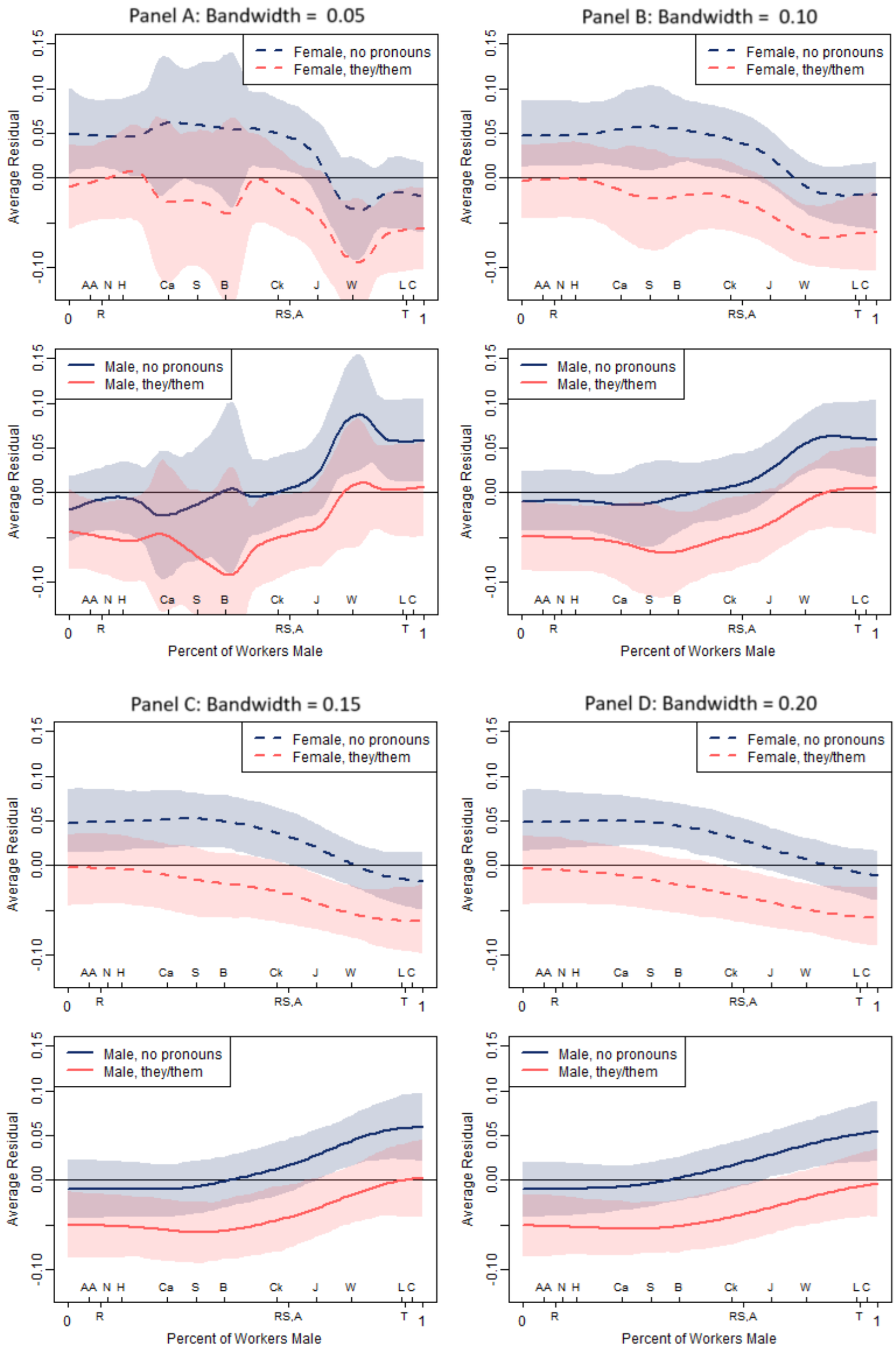

Figure A2: Average Residuals by Sex and Pronouns

Note: This figure reports group-specific average residuals from equation (2), estimated via Nadaraya-Watson kernel smoothing. Occupation sex compositions are indicated along the x-axis; see Table 1 for occupation names. The shaded areas around the average residual estimates represent 95% confidence intervals, using bootstrapping with 1,000 resampled datasets.

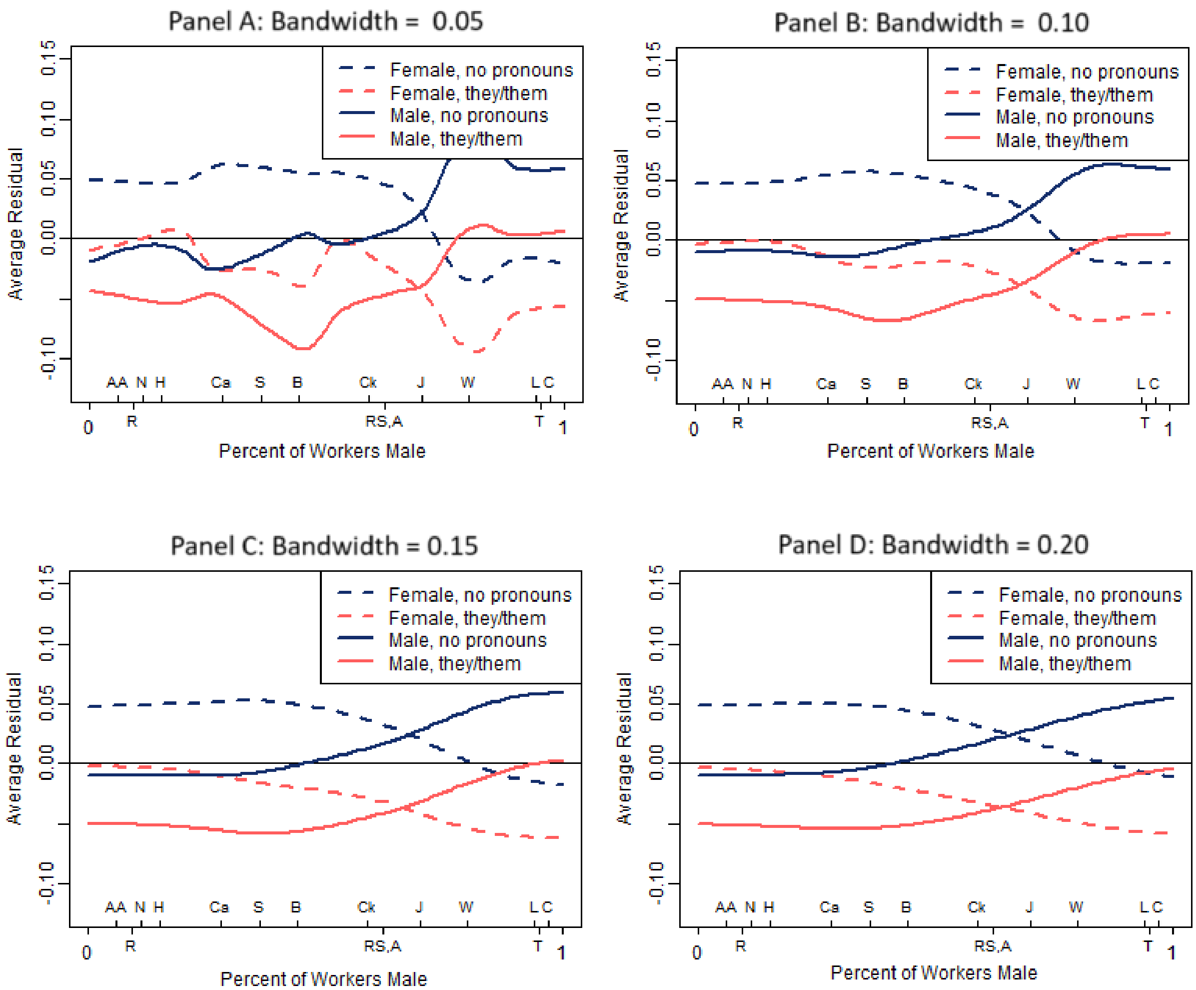

Figure A3: Average Residuals by Sex and Pronouns

Note: This figure reports group-specific average residuals from equation (2), estimated via Nadaraya-Watson kernel smoothing. Occupation sex compositions are indicated along the x-axis; see Table 1 for occupation names.