How Does the Intersection of Sex and Nonbinary Gender Identity Affect Hiring Discrimination? Evidence from a Correspondence Field Experiment

By TARYN EAMES*

Women have historically faced myriad disadvantages in the labor market leading to unequal outcomes (Goldin 1990). However, recent decades have seen significant progress in reducing such inequality (Goldin 2014). In the case of hiring discrimination, rather than always disadvantaging women, research suggests that the direction of sex-based discrimination is now based on occupation-specific factors. In particular, women are discriminated against in male-dominated occupations but men are discriminated against in female-dominated occupations (Riach and Rich 2006; Yavorsky 2019).

Existing research has focused almost exclusively on cisgender individuals, despite a sizable and growing number identifying as a gender different from their sex assigned at birth. Among gender diverse people, nonbinary identities (which exist outside the male-female binary) are the most common and fastest growing (Brown 2022). Further, compared to cisgender peers, this group faces worse labor market outcomes (Carpenter et al. 2024) as well as discrimination in hiring (Eames 2024) and other contexts (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 whether male and female nonbinary applicants face different levels of discrimination in general, motivated by research showing that LGBT people assigned male at birth often face greater labor market disadvantages than those assigned female at birth, including same-sex wage gaps (Drydakis 2021), hiring discrimination (Flage 2020), and earnings changes post-transition (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.

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I. Data

This study uses data from Eames (2024), a correspondence field experiment that identifies hiring discrimination against nonbinary applicants. In the experiment, nonbinary identity is signaled by listing "they/them" pronouns beneath the applicant's name on their resume.

Resumes were submitted in pairs to U.S. job postings in 15 occupations (described in Table 1); 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)[1]and were of similar quality. Eames (2024) describes full experimental details.

Table 1—: Occupations

Occupation	% Male	Category	N
Admin Assistant	6	F Dominated	365
Receptionist	9	F Dominated	500
Nursing Assistant	11	F Dominated	642
Housekeeper	15	F Dominated	380
Cashier	28	F Dominated	316
Server	36	Mixed	332
Baker	44	Mixed	159
Cook	59	Mixed	573
Retail Salesperson	62	Mixed	834
Assembler	62	Mixed	271
Janitor	70	M Dominated	379
Warehouse Worker	80	M Dominated	552
Landscaper	94	M Dominated	358
Truck Driver	95	M Dominated	663
Construction Worker	97	M Dominated	356

Worker sex composition data is from the 2019 American Community Survey (U.S. Census Bureau 2022). Occupation categories were pre-specified—"F Dominated" is female-dominated; "M Dominated" is male-dominated.

II. Empirical Strategy

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

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

where y_{iocj} 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 discloses "they/them" pronouns, F_i equals one if the applicant has a female-sounding name, X_i and Z_j are vectors of resume and job posting characteristics (see the Appendix), and (η_o, δ_c) are occupation and city fixed effects. Coefficient γ_2 represents the difference in discrimination against nonbinary applicants with female- compared to male-sounding names.

To estimate whether patterns of sex-based discrimination differ when applicants are presumed cisgender versus nonbinary, I run the following linear probability model separately for those who disclose "they/them" pronouns and those who do not disclose pronouns:

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

where MD_j equals one for male-dominated occupations. Coefficient λ_1 represents the impact of having a female-sounding name (versus a male-sounding name) in female-dominated and mixed occupations; λ_2 reflects the impact in male-dominated occupations. Alternative approaches are reported in the Appendix .[2]

Finally, to assess if applicants are doubly penalized when they are both the non-dominant sex and also disclose "they/them" pronouns, I

[1]Male: Marcus, Patrick, Joel, Jeremy, Parker, Adrian; female: Lindsay, Jasmine, Hannah, Leah, Marisa, Gina.

[2]The Appendix presents two alternatives: one interacting (F_i, NB_i) with FD_j (a female-dominated indicator), and another pooling observations with a triple interaction (F_i, NB_i, MD_j). I also explore a semi-parametric approach using kernel smoothing.

run the following linear probability model:

$$(3)\quad y_{iocj} = \xi_1 NB_i + \xi_2 ND_i + \xi_3 [NB_i \cdot ND_i] + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj}$$

where ND_i equals one when an applicant is the non-dominant sex. Coefficient ξ_3 reflects how intersecting identities impact discrimination: zero indicates additive effects, below zero suggests disproportionate increases, and above zero implies a mitigating effect.

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, results suggest that there are minimal differences in the extent of discrimination faced by male and female nonbinary applicants, 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
Resume Controls	✓
Job Controls	✓
Occupation Fixed Effects	✓
City Fixed Effects	✓

Note: This table reports select coefficient estimates from equation (1), 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.

Figure 1 illustrates these results, displaying raw positive response rates for each group. Matching what is reported in Table 2, this Figure indicates that nonbinary applicants face discrimination both when implied male and female; discrimination magnitude appears to be similar for both groups.

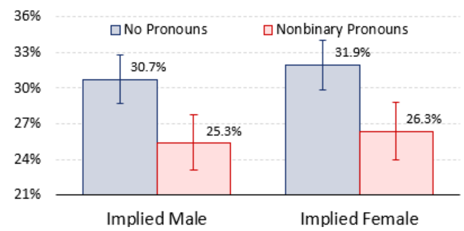

Figure 1. : Positive Employer Response Rates (by Sex and Pronoun Disclosure)

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.

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 point terms (recall that due to nonbinary discrimination, these applicants have a lower baseline employer response rate). Applicants with female-sounding names are 4.1 percentage points (17%) more likely than those with male-sounding names to receive positive responses in female-dominated and mixed occupations, but 6.9 percentage points (26%) less likely in male-dominated occupations. Thus, when it comes to occupation sex composition, nonbinary applicants face discrimination in the same direction as cisgender applicants with the same name-implied sex. Although statistical power is limited, estimated magnitudes are nearly identical. These findings are consistent with alternative specifications detailed in the Appendix, including models which pool observations and include a triple interaction term.

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
Panel C: Controls included in Panels A and B	
Resume Controls	✓
Job Controls	✓
Occupation Fixed Effects	✓
City Fixed Effects	✓

Note: This table reports select coefficient estimates from equation (2), 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.

Figure 2 illustrates these results, displaying raw positive response rates for each group, by occupation category. As reported in Table 3, this Figure suggests that nonbinary applicants experience the same direction of discrimination given occupation category. For those who list nonbinary pronouns and no pronouns alike, applicants who are implied female experience a penalty relative to those implied male in male-dominated occupations, but an advantage in female-dominated and mixed occupations.

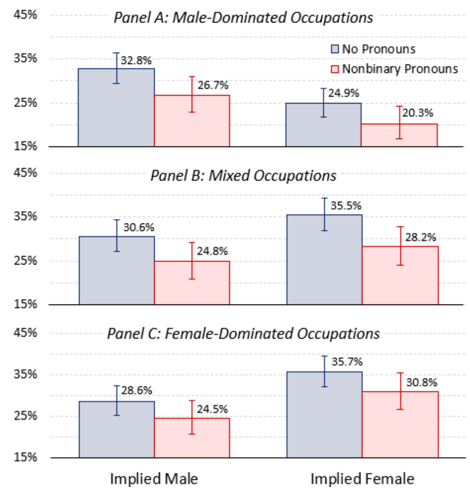

Figure 2. : Positive Employer Response Rates (by Sex, Pronoun Disclosure, and Occupation Type)

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.

Table 4 presents the results of equation (3). Results show that applicants who are minoritized once face a penalty of 6.7 percentage points (19%) for being the non-dominant sex or 6.2 percentage points (18%) for disclosing "they/them" pronouns. Applicants with intersecting identities experience both penalties, alongside a 1.5 percentage point mitigating effect (though this estimate is statistically insignificant with a wide confidence interval).

As such, there is insufficient power to determine whether discrimination builds additively or follows another pattern. However, results show that discrimination is significantly larger when applicants are minoritized on both bases. In this case, discrimination grows to 11.4 percentage points (33%)—a sizable increase, and statistically larger than either individual penalty, as confirmed by a Wald test evaluating linear combinations of coefficients (details in the Appendix).

Thus, applicants who are minoritized on the basis of both sex and nonbinary gender identity face double discrimination. Figure 2 further illustrates this pattern, showing separate penalties for being the non-dominant sex and for disclosing "they/them" pronouns, which combine when these identities intersect.

Table 4—: Double Discrimination

	Coefficient Estimate
Non-Dominant Sex	-0.067 *** (0.015) [-0.096, -0.038]
"they/them"	-0.062 *** (0.012) [-0.085, -0.039]
Non-Dominant Sex × "they/them"	0.015 (0.016) [-0.016, 0.046]
Observations	6,680
Resume Controls	✓
Job Controls	✓
Occupation Fixed Effects	✓
City Fixed Effects	✓

Note: This table reports select coefficient estimates from equation (3), where the dependent variable equals one if the applicant received a positive employer response. Males are the non-dominant sex in female-dominated and mixed occupations; females in male-dominated occupations. 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 novel evidence on how the intersection of sex and nonbinary gender identity influences hiring discrimination, particularly across occupations with varying sex compositions. First, I find no significant difference in the magnitude of discrimination faced by nonbinary applicants with male- and female-sounding names. This is notable because, among LGBT groups, those assigned male at birth are often found to experience greater penalties related to their sexual orientation or gender identity.

Second, applicants who disclose "they/them" pronouns experience trends in hiring discrimination similar to presumably cisgender applicants with the same name-implied sex. That is, applicants with female-sounding names are discriminated against in male-dominated occupations while those with male-sounding names are discriminated against in female-dominated and mixed occupations. These findings suggest that disclosing "they/them" pronouns does not substantially shift employer perceptions of an applicant's proximity to male-ness or female-ness. However, alternative explanations cannot be ruled out.

Finally, I find that applicants who are both the non-dominant sex and also disclose "they/them" pronouns face more discrimination than those who are minoritized across only one dimension. This highlights the importance of considering intersecting identities to capture the distinct ways multiple sources of bias can influence hiring outcomes.

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Supplemental Appendix

This Appendix includes:

- **Control Variables:** Tables A2 and A3 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. Two alternative specifications are run here, one including those interactions, and one replacing interactions with the percent of an occupation's workers who are male:

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

  Results for are presented in Table A4. 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:

  $$(4) \quad y_{iocj} = \lambda_1 F_i + \lambda_2[F_i \cdot MD_j] + \gamma_1 NB_i + \gamma_2[NB_i \cdot MD_j] \\ + \xi_1[F_i \cdot NB_i] + \xi_2[F_i \cdot NB_i \cdot MD_j] + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj}$$

  $$(4)' \quad y_{iocj} = \lambda_1 F_i + \lambda_2[F_i \cdot PM_j] + \gamma_1 NB_i + \gamma_2[NB_i \cdot PM_j] \\ + \xi_1[F_i \cdot NB_i] + \xi_2[F_i \cdot NB_i \cdot PM_j] + X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj}$$

  where in equation (4)$'$ 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 A5 and A6. 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).

- **Additional Semi-Parametric Results:** Equations (2), (2)$'$, and (4) 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:

$$(5) \quad y_{iocj} = X_i'\beta_1 + Z_j'\beta_2 + \eta_o + \delta_c + \varepsilon_{iocj}$$

From (5) 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 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 non-linearly estimates how occupation sex composition affects employer response, allowing unique patterns for each group.

Results are shown in Figures A1 and A2, which present 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. While precision is low, results visually suggest that the parametric assumptions associated with equation (2) and (4) are reasonable: the proposed step-function relationship appears to hold. Results are also consistent with those shown in the main paper: 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 an approximately consistent penalty across all compositions (i.e., the same male and female curves are shifted down).

Tables

Table A1: Occupations

Occupation	% Male	Category	N
Admin Assistant (AA)	6	F Dominated	365
Receptionist (R)	9	F Dominated	500
Certified 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.

Table A2: 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 A3: 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 A4: 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
Panel C: Controls included in Panels A and B	
Resume Controls	✓
Job Controls	✓
Occupation Fixed Effects	✓
City Fixed Effects	✓

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 A5: 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
Resume Controls	✓
Job Controls	✓
Occupation Fixed Effects	✓
City Fixed Effects	✓

Note: This table reports coefficient estimates from equation (4), 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 A6: 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
Resume Controls	✓
Job Controls	✓
Occupation Fixed Effects	✓
City Fixed Effects	✓

Note: This table reports coefficient estimates from equation $(4)'$, 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

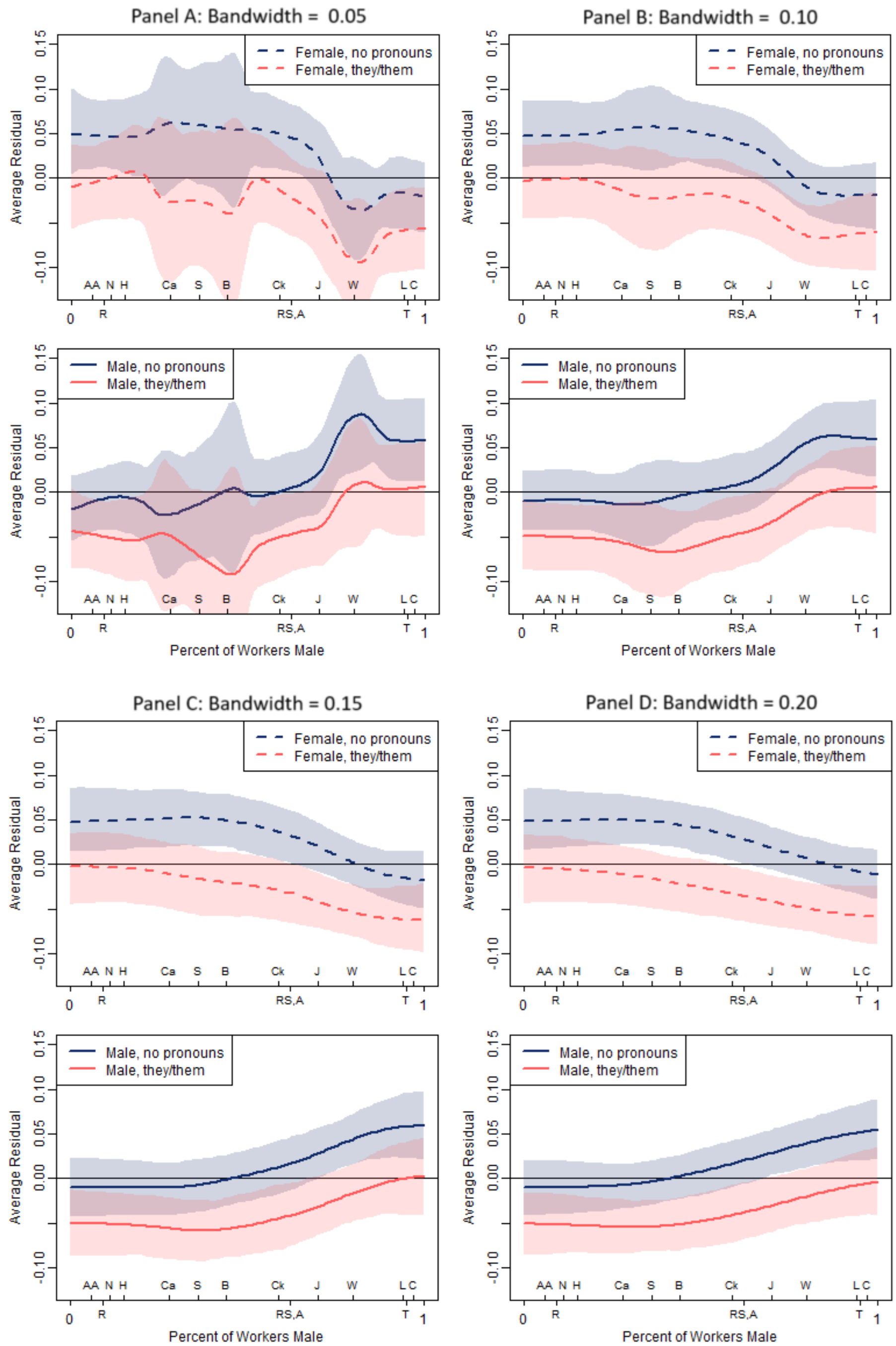

Figure A1: Average Residuals by Sex and Pronouns

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 A1 for occupation names. The shaded areas around the average residual estimates represent 95% confidence intervals, using bootstrapping with 1,000 resampled datasets.

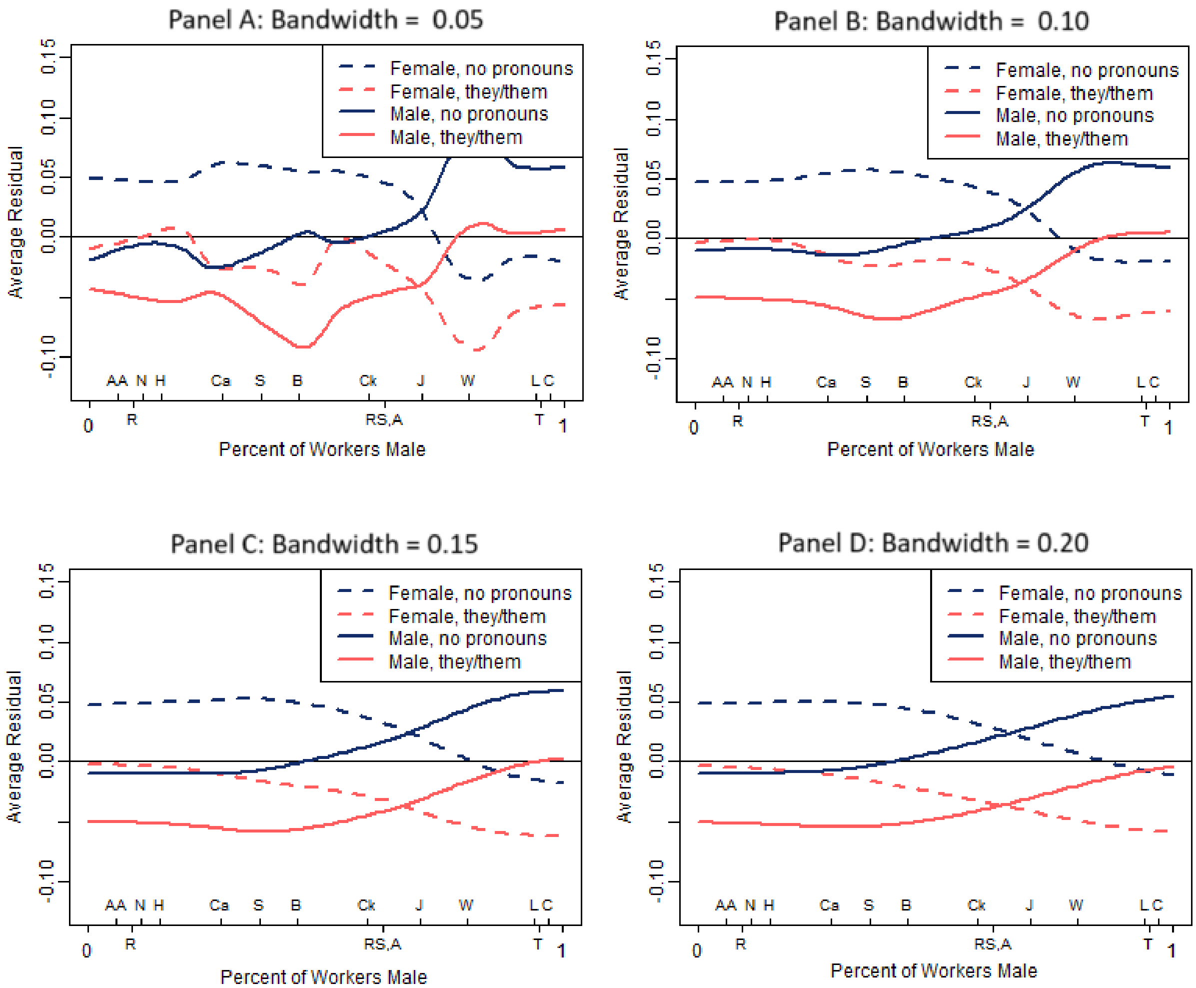

Figure A2: Average Residuals by Sex and Pronouns

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 A1 for occupation names.