Intersectionality in Hiring Discrimination: The Case of Sex and Nonbinary Gender Identities in a Range of Low Skill Occupations

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, 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 are discriminated against in male-dominated occupations, the opposite is true for men (Riach and Rich 2006; Yavorsky 2019; Cortina, Rodríguez and González 2021).

This literature has historically focused on cisgender people only. However, it is becoming increasingly common for people to identify with a gender different from their sex assigned at birth; this includes nonbinary identities that exist outside the male-female binary. In the United States, an estimated 1.2 million adults identify as nonbinary, with 76% aged 18 to 29 (Wilson and Meyer 2021). Understanding patterns in discrimination against nonbinary people is crucial, as these individuals experience significantly worse labor market outcomes than cisgender individuals (Shannon 2022; Carpenter et al. 2024). Further, there is evidence that nonbinary people experience discrimination in the labor market (Eames 2024) and in other contexts (Fumarco et al. 2024).

* PhD Candidate, Department of Economics, University of Toronto, 150 St. George Street, Toronto, Ontario, Canada (email: taryn.eadie@mail.utoronto.ca). This study could not have been completed without tireless research assistance from Siu Lun Cheong, Hanru He, YuHui Li, Minh Thuy Phi, and Sarah Zahir. I am grateful to Patrick Button, David Price, and Philip Oreopoulos for insightful suggestions and feedback.

This paper contributes to the literature by examining how the intersection of sex and nonbinary gender identity influences discrimination across occupations with varying sex compositions. Do patterns in sex-based discrimination influence cisgender people and those disclose "they/them" pronouns differently? The answer is ex-ante ambiguous: such disclosure may alter how employers perceive an applicant's proximity to male-ness or female-ness. For example, applicants with male-sounding names who disclose nonbinary pronouns might be perceived as "more female," either due to employer uncertainty about their sex or assumptions of femininity. This could mitigate sex-based discrimination in female-dominated occupations or reduce the male advantage in male-dominated ones. As such, nonbinary individuals may face distinct trends in sex-based discrimination.

I find that in the context of low-skill occupations with varying sex compositions, nonbinary applicants face discrimination patterns resembling those of cisgender applicants with the same name-implied sex. In addition, discrimination appears to be additive: applicants who are both the non-dominant sex and 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 listing "they/them" pronouns below an applicant's name on their resume signals identity. Resumes were submitted to job postings across 15 occupations. Occupations are described in Table

1: they were chosen to vary in sex composition and pre-specified as female-dominated, mixed, or male-dominated (Eames 2023).

Table 1—: Occupations

Occupation	% Male	Category	N
Admin Assistant (AA)	6	F Dominated	436
Receptionist (R)	9	F Dominated	598
Nursing Assistant (N)	11	F Dominated	762
Housekeeper (H)	15	F Dominated	458
Cashier (Ca)	28	F Dominated	354
Server (S)	36	Mixed	400
Baker (B)	44	Mixed	186
Cook (Ck)	59	Mixed	692
Retail Salesperson (RS)	62	Mixed	1000
Assembler (A)	62	Mixed	332
Janitor (J)	70	M Dominated	434
Warehouse Worker (W)	80	M Dominated	670
Landscaper (L)	94	M Dominated	426
Truck Driver (T)	95	M Dominated	792
Construction Worker (C)	97	M Dominated	430

Worker sex composition data is from the 2019 American Community Survey. "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)[1] and were of similar quality. Eames (2024) includes full experimental details.

II. Empirical Strategy

To estimate discrimination on the basis of applicant sex and "they/them" pronoun disclosure, I first run the following linear probability model:

$$(1) \quad y_{ij} = \eta_1 F_i + \eta_2 [F_i \cdot MD_j] + \gamma_1 NB_i + \gamma_2 [NB_i \cdot MD_j] + X_i' \beta_1 + Z_j' \beta_2 + \varepsilon_{ij}$$

where y_{ij} equals 1 when applicant i receives a positive response from job posting j, F_i equals 1 if the applicant is implied female (through name), MD_j equals 1 if the occupation is male-dominated, NB_i equals 1 if the resume lists "they/them" pronouns, X_i and Z_j are vectors of resume and job posting characteristics that may influence baseline employer response (see the Online Appendix), and ε_{ij} is an error term.[2]

This specification identifies the independent effects of applicant sex and pronoun disclosure on employer response, when each is separately interacted with occupation sex composition categories. However, it requires a strong assumption: that name-implied sex influences presumably cisgender applicants and those who disclose "they/them" pronouns similarly in male- and female-dominated occupations. This may not hold, since nonbinary pronoun disclosure could influence an applicant's perceived proximity to male-ness or female-ness.

To address this, I 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:

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

From (2) I compute residuals $(y_{ij} - \hat{y}_{ij})$, 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).[3] This is done separately for four groups: males and females who disclose

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

[2]In the Online Appendix, an alternative specification $(1)'$ is investigated, where F_i and NB_i are additionally interacted with FD_j (an indicator variable that equals 1 if an occupation is female-dominated). Results are consistent between (1) and $(1)'$—for simplicity, I discuss results associated with (1) here.

[3]This smoothing is implemented using the locpoly() function from the KernSmooth package in R (Wand and Jones, 1995).

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

III. Results

Table 2 shows the results of equation (1).

Table 2—: Discrimination Estimates

	Coefficient Estimate
Female	0.049 ** (0.016) [0.018, 0.081]
Female × Male Dominated	-0.121 *** (0.026) [-0.173, -0.069]
"they/them"	-0.053 *** (0.010) [-0.073, -0.033]
"they/them" × Male Dominated	-0.005 (0.022) [-0.040, 0.041]
Observations	7,970
Resume Controls	✓
Job Controls	✓

This table reports coefficient estimates from equation (1). The dependent variable equals 1 if the applicant received a positive employer response.Standard errors are clustered at the job posting level for all regressions, and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 0.1%, ** 1%, * 5% level.

Estimates indicate that females are 4.9 percentage points (14%) more likely than males to receive a positive response in female-dominated and mixed occupations. This advantage reverses in male-dominated occupations, where males are 7.2 percentage points (22%) more likely to receive a positive response. Independently, in all occupations, applicants who disclose "they/them" pronouns are 5.3 percentage points (17%) less likely to receive a positive response than those who do not. Note that by construction, equation (1) assumes independence between sex and nonbinary gender identities in terms of how sex composition influences employer response.

To investigate whether patterns of sex-based discrimination are different for presumed cisgender applicants and those who disclose "they/them" pronouns, 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. Recall that residuals above (below) zero indicate that predicted positive employer response is systematically underestimated (overestimated):

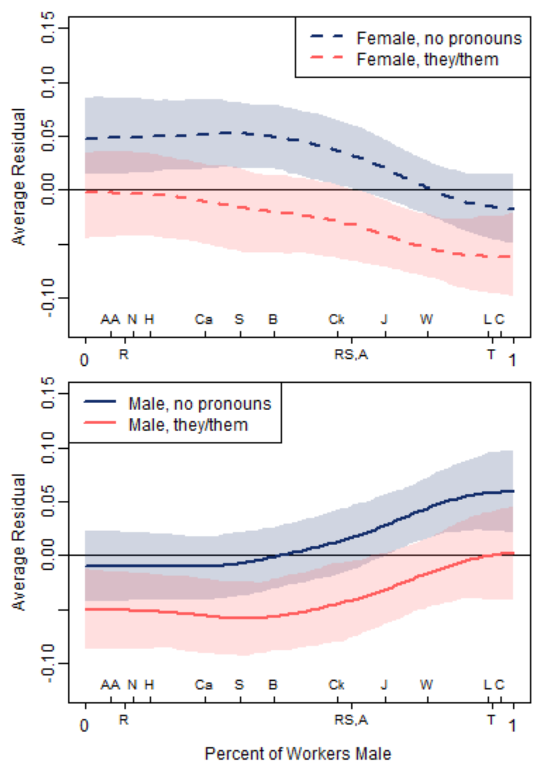

Figure 1. : Average Residuals by Sex and Pronouns

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. Kernel-smoothed estimates are generated using a bandwidth of 0.15; results using alternative bandwidths are shown in Figure A1 in the Online Appendix, and are consistent with the above. The shaded areas around the average residual estimates represent 95% confidence intervals, using bootstrapping with 1,000 resampled datasets.

Consistent with Table 2, these semi-parametric estimates show that females have higher positive employer response rates than males in female-dominated and mixed occupations, but that this advantage reverses in male-dominated occupations. Notably, residual trends for applicants with female-sounding names are similar whether or not they disclose nonbinary pronouns—as are the trends for those with male-sounding names. This suggests that disclosing "they/them" pronouns does not alter the relationship in discrimination between an applicant's name-implied sex and the occupation's sex composition. Instead, disclosure appears to impose a consistent penalty across all compositions (i.e., the same male and female curves are shifted down when an applicant discloses "they/them" pronouns).

Figure 2 presents the same semi-parametric relationships, organized differently:

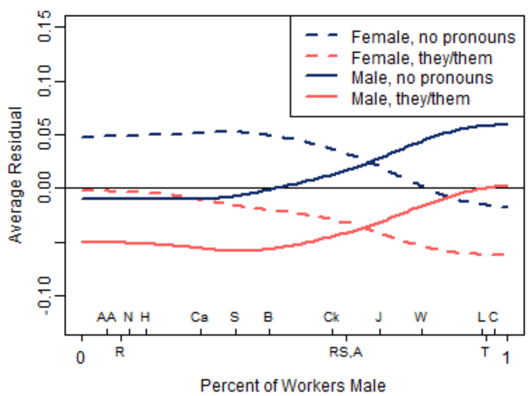

Figure 2. : Average Residuals by Sex and Pronouns

This figure reports group-specific average residuals from Equation (2), estimated via Nadaraya-Watson kernel smoothing based on the percent of workers male in an occupation. Occupation sex compositions are indicated along the x-axis; see Table 1 for occupation names. Kernel-smoothed estimates are generated using a bandwidth of 0.15; results using alternative bandwidths are shown in the Figure A2 in the Online Appendix, and are consistent with the above.

This demonstrates the apparent existence of double discrimination: applicants are penalized first 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 doubly penalized. For example, in male-dominated occupations, females face a baseline penalty, achieving response rates similar to males who disclose nonbinary pronouns. If these applicants additionally disclose "they/them" pronouns, they receive a second penalty associated with disclosure. Similarly, in female-dominated occupations, males face baseline penalties and are doubly penalized when additionally disclosing nonbinary pronouns.

Figures 1 and 2 support the parametric assumptions underlying equation (1). Hence, Table 2 indicates that applicants with female-sounding names who apply to male-dominated occupations and disclose "they/them" pronouns face positive employer response rates that are 13.1 percentage points (45%) lower than males who do not disclose pronouns. This penalty is 10.6 percentage points (33%) for males who disclose "they/them" pronouns and apply to female-dominated occupations. Further bolstering the assertion that the parametric assumptions of equation (1) are reasonable, results are consistent with those obtained by running equation (1) while including applicants who disclose "they/them" pronouns only—shown in Table 3.

Table 3—: Discrimination Estimates (Nonbinary Applicants Only)

	Estimate
Female	0.042 * (0.021) [0.000, 0.084]
Female × Male Dominated	-0.111 ** (0.035) [-0.179, -0.043]
Observations	2,695
Resume Controls	✓
Job Controls	✓

This table reports coefficient estimates from equation (1), for applicants who disclose "they/them" pronouns only. The dependent variable equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 0.1%, ** 1%, * 5% level.

IV. Discussion

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

These findings highlight the importance of considering intersectionality when estimating discrimination. In this study, I find that discrimination accumulates independently and additively; however, this is not always or even typically the case (Fumarco et al. 2024; Lahey and Oxley 2021). People contain multitudes, and acknowledging these complexities is essential to fully understand and address discrimination.

REFERENCES

Carpenter, Christopher S, Donn L Feir, Krishna Pendakur, and Casey Warman. 2024. “Nonbinary gender identities and earnings: Evidence from a national census.” National Bureau of Economic Research Working Paper 33075.

Cortina, Clara, Jorge Rodríguez, and M. José González. 2021. “Mind the Job: The Role of Occupational Characteristics in Explaining Gender Discrimination.” Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement, 156(1): 91–110.

Eames, Taryn. 2023. “Nonbinary hiring discrimination and the politicization of pronouns: A resume audit study.” AEA RCT Registry. May 17, 2023. https://doi.org/10.1257/rct.11183-2.0.

Eames, Taryn. 2024. “Taryn versus Taryn (she/her) versus Taryn (they/them): A field experiment on pronoun disclosure and nonbinary hiring discrimination.” SSRN Working Paper. April 11, 2024. https://papers.ssrn.com/abstract_id=4694653.

Fumarco, Luca, Benjamin J. Harrell, Patrick Button, David J. Schwegman, and E Dils. 2024. “Gender Identity-, Race-, and Ethnicity-Based Discrimination in Access to Mental Health Care.” American Journal of Health Economics, 10: 182.

Goldin, Claudia. 1990. Understanding the gender gap: An economic history of American women. New York: Oxford University Press.

Goldin, Claudia. 2014. “A Grand Gender Convergence: Its Last Chapter.” American Economic Review, 104(4): 1091–1119.

Lahey, Joanna N., and Douglas R. Oxley. 2021. “Discrimination at the intersection of age, race, and gender: Evidence from an eye-tracking experiment.” Journal of Policy Analysis and Management, 40(4): 1083–1119.

Riach, Peter A, and Judith Rich. 2006. “An Experimental Investigation of Sexual Discrimination in Hiring in the English Labor Market.” The B.E. Journal of Economic Analysis Policy, 6(2): 0000102202153806371416.

Shannon, Matthew. 2022. “The labour market outcomes of transgender individuals.” Labour Economics, 77: 102006.

Wand, M. P., and M. C. Jones. 1995. Kernel Smoothing. Chapman & Hall/CRC.

Wilson, Bianca D.M., and Ilan H. Meyer. 2021. “Brief: Nonbinary LGBTQ adults in the United States.” The Williams Institute. https://williamsinstitute.law.ucla.edu/nonbinary-adults/. Accessed October 18, 2023.

Yavorsky, Jill E. 2019. “Uneven Patterns of Inequality: An Audit Analysis of Hiring-Related Practices by Gendered and Classed Contexts.” Social Forces, 98(2): 461–492.

Online Appendix

This Appendix includes:

- **Control Variables:** Table A1 contains a detailed description of all variables included in the vector of resume controls (X_i). Table A2 contains a detailed description of all variables included in the vector of job posting controls (Z_j).

- **Alternative Linear Probability Results:** Recall equation (1) below, used in the linear probability specification presented in the main paper:

$$(1) \quad y_{ij} = \eta_1 F_i + \eta_2 [F_i \cdot MD_j] + \gamma_1 NB_i + \gamma_2 [NB_i \cdot MD_j] + X_i' \beta_1 + Z_j' \beta_2 + \varepsilon_{ij}$$

  This equation does not include interactions between F_i and FD_j or NB_i and FD_j. To address this, an alternative specification is run here, including those interactions:

$$(1)' \quad y_{ij} = +\eta_1 F_i + \eta_2 [F_i \cdot FD_j] + \eta_3 [F_i \cdot MD_j] + \gamma_1 NB_i + \gamma_2 [NB_i \cdot FD_j] + \gamma_3 [NB_i \cdot MD_j] + X_i' \beta_1 + Z_j' \beta_2 + \varepsilon_{ij}$$

  Results for all applicants are presented in Table A3. For females and nonbinary people, there is no statistically significant difference in positive employer response in female-dominated and mixed occupations. Hence, for simplicity and precision, in the main paper (1) is shown only. Results including nonbinary applicants only are presented in Table A4. Again, there is no statistical difference between positive employer response in female-dominated and mixed occupations. Focusing on this smaller subset and including three occupation categories reduces power and precision. This is another reason why the main paper uses specification (1) over (1)$'$.

- **Alternative Semi-Parametric Results:** Recall that in the main paper, kernel estimation used a bandwidth of 0.15; Figures A1 and A2 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
Occupation	Fixed Effect	Fixed effects for each of the 15 occupations being applied for
Location	Fixed Effect	Fixed effects for each of the six cities being applied within
Research Assistant	Fixed Effect	Fixed effects for each Research Assistant who found and applied to the job posting
Sent first	Indicator	Equals 1 if the resume was sent first
Resume lag	Discrete	Equals 0 if the resume was sent first, and the hours between the first and second application if the resume was sent second
Resume lag^2	Discrete	Above squared
GED	Indicator	Equals 1 if the applicant achieved a GED
Associate's	Indicator	Equals 1 if the applicant achieved an Associate's degree
Bachelor's	Indicator	Equals 1 if the applicant achieved a Bachelor's degree
High Score High School	Indicator	Equals 1 if the applicant went to a high school with test scores rated 'A' by Niche
Low Score High School	Indicator	Equals 1 if the applicant went to a high school with test scores rated 'C' or below by Niche
Worked in HS	Indicator	Equals 1 if the applicant worked during high school
Years relevant	Discrete	Equals the number of years of "relevant" work experience.
Years relevant^2	Discrete	Above squared
Current relevant	Indicator	Equals 1 if the applicant's most recent work experience is "relevant"
Current most common	Indicator	Equals 1 if the applicant's most recent work experience is "most common"
Current common	Indicator	Equals 1 if the applicant's most recent work experience is "common"
Prior most common	Discrete	Equals the years of "most common" experience, omitting most recent experience
Prior most common^2	Discrete	Above squared
Prior common	Discrete	Equals the years of "common" experience, omitting most recent experience
Prior common^2	Discrete	Above squared
Summary	Indicator	Equals 1 if the resume includes a summary or objective section
Skill: communication	Indicator	Equals 1 if the applicant's resume lists "clear communicator" as a skill
Skill: computer	Indicator	Equals 1 if the applicant's resume lists "computer skills (tech savvy)" as a skill
Skill: detail oriented	Indicator	Equals 1 if the applicant's resume lists "detail oriented" as a skill
Skill: fast learner	Indicator	Equals 1 if the applicant's resume lists "fast learner" as a skill
Skill: fast-paced	Indicator	Equals 1 if the applicant's resume lists "thrives in fast-paced settings" as a skill
Skill: leader	Indicator	Equals 1 if the applicant's resume lists "leadership abilities" as a skill
Skill: organized	Indicator	Equals 1 if the applicant's resume lists "organized and efficient" as a skill
Skill: team player	Indicator	Equals 1 if the applicant's resume lists "team player" as a skill
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
Occupation	Fixed Effect	Fixed effects for each of the 15 occupations being applied for
Location	Fixed Effect	Fixed effects for each of the six cities being applied within
Research Assistant	Fixed Effect	Fixed effects for each Research Assistant who found and applied to the job posting
Estimated applications	Discrete	Equals the lower bound of the range of applicants estimated to have applied to the job posting (this was scraped from the job board website, values range from 1 to 1,496). Equals 0 if the job board website did provide an estimated application range
Estimated applications^2	Discrete	Above squared
Missing estimated applications	Indicator	Equals 1 if the job board did not provide an estimated application range
Relative income	Continuous	The lower bound of estimated income expressed as a percent of the occupation-specific average
Relative income^2	Continuous	Above squared
Relative income difference	Continuous	The difference between the upper and lower estimated income bounds expressed as a percent of the occupation-specific average
Relative income difference^2	Continuous	Above squared
Missing estimated income	Indicator	Equals 1 if the job posting did not include an associated income range

Table A3: Discrimination Estimates

	Coefficient Estimate
Female	0.046 * (0.023) [0.001, 0.090]
Female × Female Dominated	0.007 (0.031) [-0.055, 0.068]
Female × Male Dominated	-0.117 *** (0.031) [-0.178, -0.056]
"they/them"	-0.060 *** (0.015) [-0.090, -0.029]
"they/them" × Female Dominated	0.013 (0.022) [-0.030, 0.055]
"they/them" × Male Dominated	0.002 (0.022) [-0.040, 0.044]
Observations	7,970
Resume Controls	✓
Job Controls	✓

This table reports coefficient estimates from equation (1)$'$. The dependent variable is an indicator variable which equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 0.1%, ** 1%, * 5% level.

Table A4: Discrimination Estimates
(Nonbinary Applicants Only)

	Coefficient Estimate
Female	0.033 (0.030) [-0.026, 0.093]
Female × Female Dominated	0.017 (0.042) [-0.065, 0.099]
Female × Male Dominated	-0.102 * (0.031) [-0.183, -0.022]
Observations	2,695
Resume Controls	✓
Job Controls	✓

This table reports coefficient estimates from equation (1), for applicants who disclose "they/them" pronouns only. The dependent variable equals 1 if the applicant received a positive employer response. Standard errors are clustered at the job posting level for all regressions, and reported in parentheses. Confidence intervals are reported in square brackets. Stars indicate statistical significance: *** 0.1%, ** 1%, * 5% level.

Figures

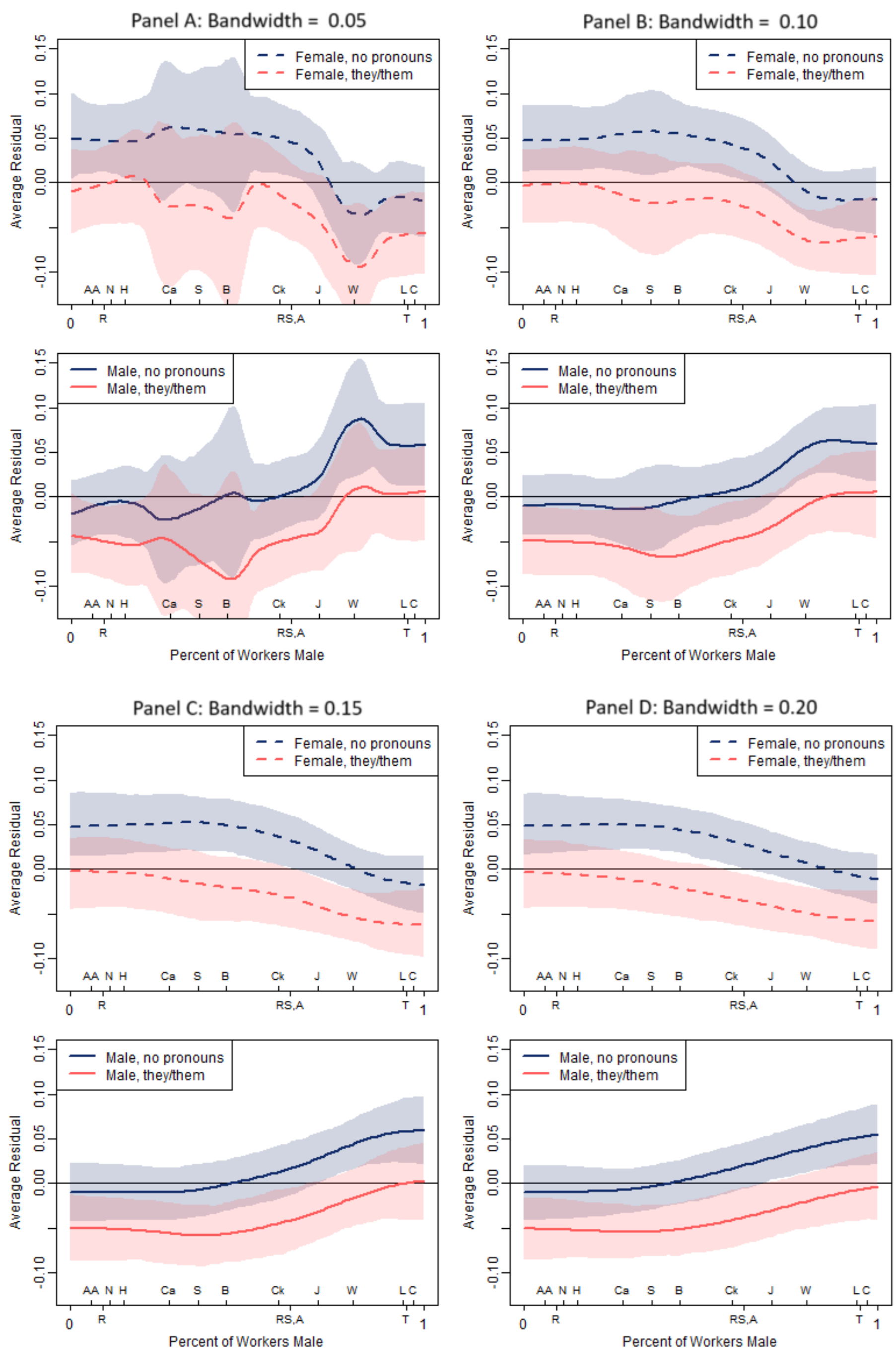

Figure A1: Average Residuals by Sex and Pronouns

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.

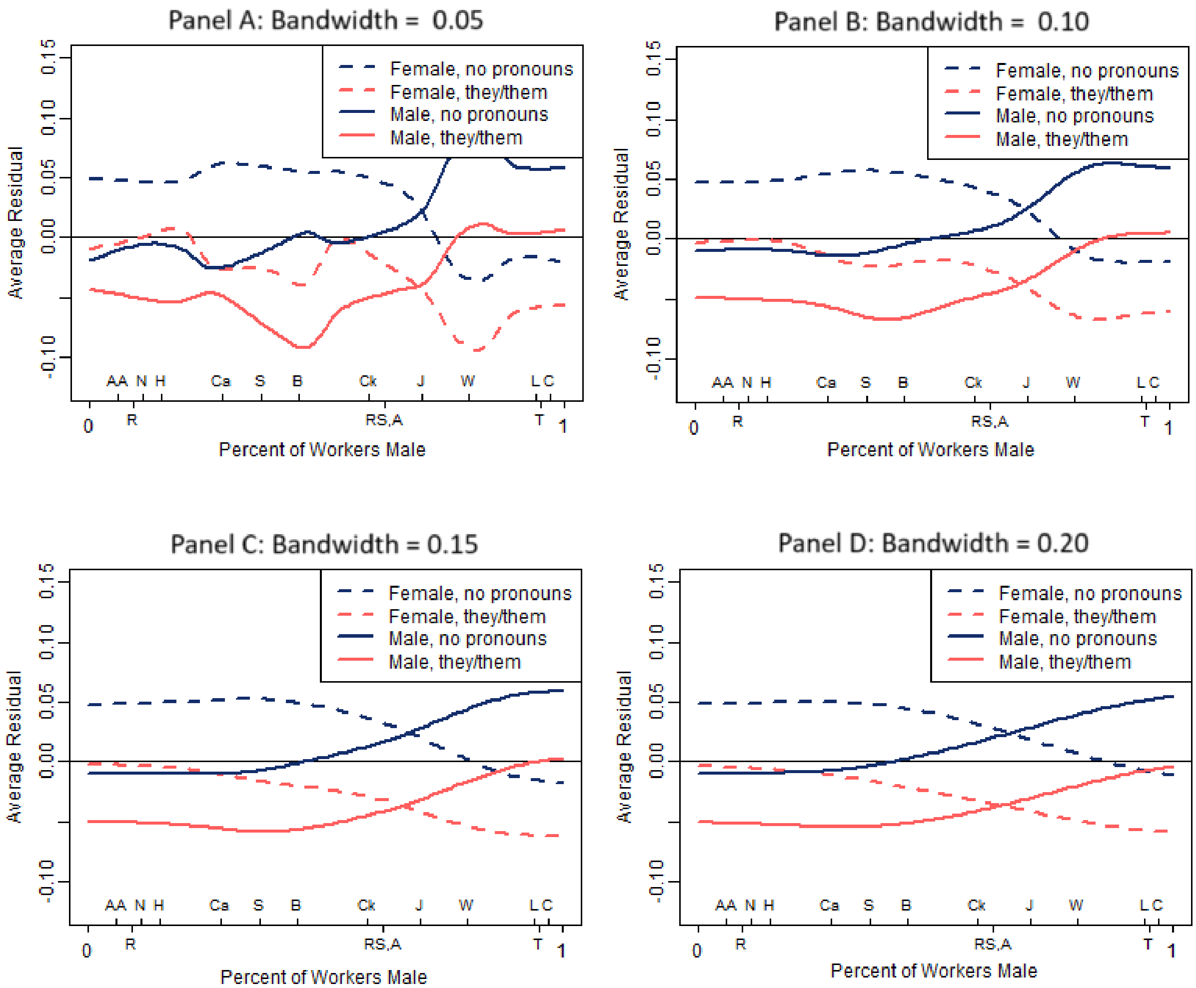

Figure A2: Average Residuals by Sex and Pronouns

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.