Hiring Discrimination Against Transgender Job Applicants in the US Labor Market*

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Abstract

We investigate the extent of hiring discrimination against transgender individuals across the United States and how it varies by transgender identity, race, and geography. Through a correspondence study with more than 5,600 applications to entry-level positions, we find that transgender individuals are 2.1 percentage points (15%) less likely to get a callback. However, this aggregate effect masks important heterogeneity: callback penalties for transgender women and non-binary applicants are substantially larger in historically Republican-leaning labor markets, at 4.4–5.8pp relative to cisgender men. While Black applicants have lower callback rates overall, we do not find evidence that discrimination by transgender identity differs by race. We do not find evidence that the recent introduction or passage of anti-transgender legislation is associated with greater discrimination against transgender applicants. These results highlight that underlying political climates are more strongly associated with employer discrimination toward transgender applicants than increased salience due to anti-transgender legislation.

JEL codes: C93, J71, J16, J15, J23
Keywords: hiring discrimination; correspondence study; transgender; gender identity; race; political climate

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This study is approved under protocol STUDY00002218 by the University of Vermont Institutional Review Board. This study was pre-registered at the AEA RCT Registry as "Hiring Discrimination Against Transgender Job Applicants in the US Labor Market," #AEARCTR-0013199. De-identified data and replication code will be made publicly available upon publication.

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1 Introduction

Transgender individuals in the United States face employment discrimination across occupations and sectors, harming their well-being and exacerbating economic inequalities with the general population (Grant et al., 2011; Fumarco et al., 2024; Abbate et al., 2024). Among these disparities are lower earnings, higher poverty rates, and higher unemployment rates (Schilt and Wiswall, 2008; Carpenter et al., 2020; Shannon, 2022; Carpenter et al., 2024; Badgett et al., 2024; Campbell et al., 2025). However, experiences are not uniform, reflecting differences in treatment by gender identity and regional differences in attitudes and policies toward transgender individuals.

This study aims to understand how gender identity, race, and geography affect employer demand for transgender job applicants across the United States. We ask: how do gender identity and race affect employment discrimination, both separately and when considered together with an intersectional lens? Additionally, how does employment discrimination against transgender people vary by state and region within the United States, and to what extent does it vary with state legislation and local political climates?

We conduct a correspondence study in which we submit more than 5,600 applications to entry-level postings in 48 markets across 27 states in 2023–2024, focusing on the food service and retail sectors. We vary gender identity by using gender-specific names for cisgender men and women and then indicate transgender identity by using those same names alongside a phrase that indicates a legal name of a different gender. Conditional on gender, we use traditionally White names and traditionally Black names to signal race (Bertrand and Mullainathan, 2004).

In aggregate, transgender applicants are 15% (2.1 percentage points) less likely than cisgender applicants to receive a callback. This finding is consistent with previous studies (Campbell et al., 2025), although the magnitude is more modest. However, this pooled comparison masks important heterogeneity by gender identity and across labor markets. We find no evidence of discrimination against transgender men, consistent with recent research that finds penalties are concentrated among transgender women (Campbell et al., 2024; Geijtenbeek and Plug, 2018) and non-binary applicants (Eames, 2024; Coffman et al., 2026). Additionally, callback penalties are concentrated in relatively Republican-leaning markets. Specifically, in markets with an above-median county-level Republican vote share in the 2012–2020 presidential elections, transgender women are 5.8 percentage points less likely to receive a callback, and non-binary applicants are 4.4 percentage points less likely. In contrast, we do not find evidence that the recent introduction or passage of anti-transgender legislation predicts discrimination, suggesting that underlying attitudes, rather than policy-induced salience of transgender identity, are more strongly associated with employer behavior.

We make three contributions. First, we conduct the largest U.S. correspondence study of transgender hiring discrimination to date, with disaggregation by specific gender identity. Our design includes transgender men, transgender women, and non-binary individuals across 48 metropolitan areas in 27 states, capturing heterogeneity by local market, state, and region. Previous U.S. correspondence studies on transgender hiring discrimination are limited to one to three states (Bardales, 2013; Eames, 2024); the only nationally representative study excludes transgender men and women from its design (Kline et al., 2022). Two additional correspondence studies examine transgender discrimination outside labor markets, in rental housing (Tomlin, 2024) and mental healthcare access (Fumarco et al., 2024).

Second, we integrate race into our design, which we believe is unique in previous studies of transgender hiring discrimination. Capturing the effects of discrimination by both gender identity and race is important because Black transgender women experience worse economic outcomes overall as a result of the combined penalties for being Black, being transgender, and being a woman, which are often considered in isolation (Grant et al., 2011). More broadly, a limited number of correspondence studies include both gender and race in their design (Gaddis et al., 2025). This gap is concerning because the disparities in hiring between Black and White job applicants have remained stable for nearly four decades (Quillian et al., 2017) and are currently present at some of the largest employers in the United States (Kline et al., 2024). Descriptive evidence (Grant et al., 2011; Neumark, 2018; Pedulla, 2018; Berry et al., 2024) and correspondence studies conducted on health care access (Fumarco et al., 2024) and housing access (Gaddis and DiRago, 2023) find hiring discrimination against Black workers that affirms these persistent employment gaps. When aggregating the effects of race, transgender identity, and gender, we find that Black transgender women and Black non-binary applicants have 4.5–5 percentage points lower callback rates than White cisgender men.

Third, we investigate the local predictors of employer discrimination against transgender individuals. Some areas may have higher rates of discrimination because of differences in underlying preferences, such as conservative political beliefs, which are associated with more negative attitudes (Prusaczyk and Hodson, 2020), consistent with taste-based models in which the level of local prejudice shapes labor market outcomes (Becker, 1957; Charles and Guryan, 2008). While attitudes toward transgender people in the United States grew more favorable from 2015–2020, opinions diverged along political lines (Lewis et al., 2022). As such, we measure the relationship between county-level Republican vote shares and hiring discrimination. Recent correspondence studies provide evidence that transgender discrimination is associated with higher Republican vote shares, specifically in Colorado, Utah, and Washington labor markets (Eames, 2024) and in Californian apartment rental markets (Tomlin, 2024). The recent passage of restrictive anti-transgender legislation is also associated with negative attitudes toward transgender individuals (Jaramillo et al., 2025; Roy et al., 2025), although this is before controlling for political beliefs, which may correlate with such legislation. In addition to these policies reflecting underlying voter sentiment, they may make transgender identity more salient, leading employers to believe that it is permissible to discriminate against transgender job applicants. Similarly, this rise in anti-transgender legislation could activate other identifiers correlated with discrimination, such as a disdain for pronoun use because conservatives see it as a signal of progressive beliefs. We provide new evidence that counties with high Republican vote shares in the 2012–2020 presidential elections are associated with greater levels of hiring discrimination against transgender job applicants. These results are consistent with the literature on persistent underlying preferences, but we do not find evidence that discrimination is worsened by the rise in anti-trans legislation nor lessened by increased labor-market tightness.

2 Experimental design

This study was conducted in two phases. The first phase, conducted in 2023, focused on four large labor markets—Phoenix, New York City, Houston, and Los Angeles—and included 1,100 applications that varied gender identity but not race. Additional detail on the results from this phase are discussed in Stanton (2023). The second phase was conducted in 2024 and included a broader range of markets and states, with 4,523 valid submissions.

The study includes 48 markets across 27 U.S. states from the total 417 Craigslist markets in the United States (see Appendix Table B.1). We restricted our sample to 110 "active" markets in 40 states, excluding those that received fewer than 5 postings for food positions within a two-day period. We randomly selected two-thirds of the remaining states, stratifying by state-level Republican vote shares in the 2020 presidential election and ensuring the inclusion of the four Phase 1 states. We then selected the four Phase 1 markets and up to two markets per state, with the state-specific probability of selection proportional to the number of job postings in that market. We made additional revisions when markets overlapped or there were insufficient postings upon beginning submissions. Additional details are provided in Appendix B.

2.1 Resume generation and identity signaling

We generated resumes tailored to either the food or retail industry, using standardized sets of jobs and companies that have a national presence. Applicants have experience with two entry-level positions in each industry and either a college degree from a local 4-year institution (Phase 1) or high school diploma (Phase 2) from a school in their city ranked as "average" (5–6) by GreatSchools, extending the range to 4–7 when necessary.[1]

We signaled applicant gender and race by selecting names that are particularly common to White women, Black women, White men, and Black men, using the SSA list of first names given to newborns in 2003 and 2000 U.S. Census data on surnames.[2] Gendered and racially coded names have traditionally been a signal of race in correspondence studies (Bertrand and Mullainathan, 2004), and recent literature finds that this design remains an effective signal of race, although it may also signal class (Crabtree et al., 2022).

We signaled transgender identity by including a statement near the top of each resume stating that the applicant's preferred and legal names differ, as Appendix Figure A.1 shows. For example, "My preferred name is Kenya, but my legal name is Reginald." One name was unambiguously masculine, while the other name was unambiguously feminine to establish a contrast in gender between the applicant's legal name and preferred name that signals transgender identity. We use the same set of names for legal names and preferred names.

To signal non-binary gender identity, we include the statement "(They/them)" next to the applicant name. For cisgender applicants with included pronouns, we include "(She/her)" or "(He/him)" next to the applicant name.

Correspondence study results may depend on how identity is signaled (Phillips, 2019), and there are several signals of binary transgender identity among field experiments conducted in labor markets across multiple countries (Campbell et al., 2025). Using a change in name to signal transgender identity that we employ has proven to be an effective signal in other field experiments (Granberg et al., 2020; Martínez-Alfaro et al., 2024; Tomlin, 2024; Drydakis, 2025), which also find evidence of substantial hiring discrimination against transgender job applicants. However, the legal-name statement is also a non-standard resume element, which could prompt employer concerns or hesitation unrelated to gender identity.

[1] We include both public and charter high schools, excluding magnet schools.

[2] Due to a coding error, one cisgender White female name (Mary) is based on overall popularity rather than recent popularity. Appendix Table A.1 shows that our main estimates are robust to dropping applications using this name.

This statement could provide at least three distinct signals: the applicant's transgender identity; an indication that the applicant's legal documents may not match their presented name, which could lead to additional hiring frictions; and an act of self-disclosure that could be interpreted as a social or political statement. Our estimates effectively reflect the net effect of this statement, rather than the effect of perceived transgender identity alone. However, for transgender applicants who have changed their lived but not legal name, this decision to disclose at the time of application is highly relevant.

2.2 Posting screening

We applied for entry-level food service and retail positions. Specifically, we targeted all postings listed on the food service and retail pages of the Craigslist job ads, excluding those that were (1) not entry-level (ex: manager positions that require more experience); (2) require the applicant to call, text, complete an application, write a cover letter, or go in-person to apply; and/or (3) mass positions for gig positions through firms like DoorDash and InstaCart, which require applications via an external website.

We scraped food and retail job postings weekly from all selected markets on Craigslist, removing ineligible postings and duplicates. If employers post multiple positions, we randomly selected one position to apply to.

2.3 Randomization

Stratifying by market, we randomize half of all applications to be from White applicants and half to be from Black applicants. We cross-randomize this with gender identity, such that applications are equally likely to be assigned to one of four gender identities: (1) cisgender, no pronouns; cisgender, with pronouns; transgender, binary; and transgender, non-binary.[3]

Based on race, each applicant was randomly assigned to receive one of four race-specific

[3]All Phase 1 resumes and the first batch of Phase 2 submissions (2,029 resumes in the analysis sample) are also stratified by employer, but the remainder is stratified only by market, reflecting recommendations from Phillips (2019).

names, two for men and two for women. Among the White transgender, non-binary applicants, half were randomized to receive a non-binary name.[4] For binary transgender applicants, we chose a legal name that reflected the same race but a different gender identity, so transgender men have a recognizably female legal name. Appendix Table B.3 includes the set of names used.

For each job category and market, we generated two different resume versions, which we randomly assigned so that each employer received one application from each type. Resumes were designed to be of equal quality.

Table 1 shows the distribution of applicant characteristics by gender. The first three rows show the distribution of applications across gender identity overall and by phases. Phase 1 does not include non-binary applications, while they comprise 25% of Phase 2 applications. Additionally, while the share of submissions from Black applicants is approximately 50% in Phase 2 (row 7), it is closer to 40% overall because all Phase 1 applications signaled White identity. Roughly three-quarters of applications were for food service positions, reflecting a greater share of postings in this sector, and approximately half were customer-facing.

Table 1: Applicant characteristics by gender identity

	All	Cis men	Cis women	Trans men	Trans women	Non-binary
Observations	5623	1391	1402	825	855	1150
Phase 1 N	1100	275	275	275	275	0
Phase 2 N	4523	1116	1127	550	580	1150
% Black	0.401	0.398	0.412	0.328	0.338	0.491
% Food service	0.768	0.775	0.769	0.751	0.734	0.795
% Customer facing	0.512	0.503	0.511	0.533	0.559	0.472
Callback rate	0.123	0.130	0.138	0.131	0.110	0.099

Appendix Table A.3 confirms that observable applicant characteristics are balanced across

[4] Because gender-neutral names that were distinctly Black were not available, all Black non-binary applicants had gendered names and included they/them pronouns. Gender-neutral names (e.g., Skyler Jensen, Peyton Meyer) were assigned only to White non-binary applicants. Appendix Table A.2 shows no evidence that callback rates differ by perceived name gender among non-binary applicants, although power for this test is limited.

treatment arms, with joint tests of balance shown in the final columns.

2.4 Outcomes

The key outcome variable is whether a submitted resume receives a callback from an employer. We define a callback as any e-mail, text message, or phone call to invite the applicant for an interview or to request more information. Neutral interactions, such as an employer sending a message to confirm receipt, are not considered a callback, nor are (rare) negative interactions. We considered all responses within two weeks to constitute a callback. The overall callback rate was 12.3%: 16.3% in Phase 1 and 11.3% in Phase 2.[5] Employers primarily responded through email (71.5%), some of whom also followed up by phone (8.7% overall), which was typically through text message rather than voice call. The remaining 28.5% contacted applicants only by phone.[6]

2.5 Power calculations

Our initial power calculations were based on 80% power and a 5% significance level, relying on a baseline callback rate of 19% and assuming that covariates and market fixed effects explain 10% of the variation in callback rates, reflecting Stanton (2023).

With 1,500 observations per arm in Equation 1, this provides 80% power to detect an MDE of 3.8 percentage points among non-binary applicants or pooled transgender men and transgender women. We can detect an MDE of 4.8 percentage points among transgender men and women, respectively, based on pair-wise comparisons with cisgender men. Based on simulation, for interaction effects by race, as shown in Equation 2, we have 80% power to detect an interaction effect of roughly 5.5 percentage points.

Using realized callback rates and sample sizes, we calculate ex post minimum detectable effects (MDEs) at 80% power. For the pooled transgender indicator (Column 1 of Table 2),

[5] We recorded but did not include later callbacks in Phase 2, which demonstrates that the two-week window captures 93% of all callbacks in that phase, and 97% of all callbacks received 30 days after submission.

[6] Based on Phase 2 responses.

the realized MDE is 2.8 percentage points, slightly above the observed 2.1 percentage point effect; the pooled estimate is significant at conventional levels but close to the boundary of what the design can reliably detect. For disaggregated gender identities (Column 2), MDEs range from 3.4 to 3.6 percentage points, comparable to or smaller than the ex ante calculations. The study is therefore adequately powered to detect the aggregate and White subgroup effects we report. For Black applicants separately, the identity-specific MDEs range from 5.8 to 7.4 percentage points, which exceed the observed point estimates, and the null results for Black subgroups in Table 3 should be interpreted with this power limitation in mind.

3 Empirical specifications

Our primary specification measures the differential impact of gender identity on callback rates relative to cisgender men:

$$\begin{aligned} Callback_{ijm} = \alpha + \beta_1 TransMan_{ijm} + \beta_2 TransWoman_{ijm} + \beta_3 NonBinary_{ijm} + \\ \beta_4 CisWoman_{ijm} + \gamma_1 CisPronouns_{ijm} + \gamma_2 CustFacing_{jm} + \phi_m + X'\psi + \epsilon_{ijm} \end{aligned} \tag{1}$$

where $Callback_{ijm}$ equals 1 if employer j in market m called back resume i for an interview. The indicators $TransMan$, $TransWoman$, $NonBinary$, and $CisWoman$ are equal to 1 based on the signaled gender identity in the submitted resume. $CisPronouns$ is equal to one if a cisgender applicant includes pronouns (she/her or he/him). ϕ_m represents a set of market-level fixed effects, which form our stratification cells.

We also improve the precision of our estimates by including day-of-week, week-of-submission FE, and submitter FE, captured in the vector X, which we report as a robustness table in the Appendix. Standard errors are clustered at the employer level to account for within-employer correlation across the two applications sent to each posting. In specifications that exploit market-level policy variation without market fixed effects (Equation 3), we cluster at the market level (48 clusters).[7]

To detect differences by race, we estimate a single, fully interacted model to test whether coefficients on β_1 through β_3 are each equal between Black and White applicants:

$$\begin{split} Callback_{ijm} = \alpha + \beta_1 Trans_{ijm} + \beta_2 Black_{ijm} + \beta_3 TransXBlack_{ijm} + \\ \gamma_1 CisPronouns_{ijm} + \gamma_2 CustFacing_{jm} + \phi_m + X'_{ij}\psi + \epsilon_{ijm} \end{split} \tag{2}$$

We also estimate a version of Equation 2 that disaggregates transgender applicants, $Trans$, into three groups: transgender men, transgender women, and non-binary applicants.

To examine differences in impact by political climate, we estimate Equation 3, which is similar to Equation 2 but uses a political climate variable as the interaction term, which varies at the state or market level. Additionally, we omit market-level fixed effects to avoid collinearity, and we instead control for county-level unemployment rates. We also include a Phase 1 indicator and its interaction with the policy measure because Phase 1 markets differ in both composition and baseline callback rates.

$$\begin{split} Callback_{ijm} = \alpha + \beta_1 Trans_{ijm} + \beta_2 Pol.Climate_m + \beta_3 TransXPol.Climate_{ijm} + \\ \gamma_1 CisPronouns_{ijm} + \gamma_2 CustFacing_{jm} + Y'_m\kappa + X'_{ij}\psi + \epsilon_{ijm} \end{split} \tag{3}$$

3.1 Policy heterogeneity

We then test for heterogeneity in responses based on the general political climate and passage of anti-transgender legislation. We use the state- and/or local-level Republican vote share, averaged over the 2012–2020 presidential elections as a proxy for the underlying political climate, and we show the robustness of our results to using 2016–2020 and 2020-only

[7] We also implement randomization inference as a robustness check following Young (2019) (Appendix Table A.4), and our results remain statistically significant (pooled $p = 0.015$; trans woman $p = 0.028$; non-binary $p = 0.040$).

results.[8] This approach allows us to use market- rather than state-level vote shares, which is particularly important when population centers have different voting preferences relative to the overall state. In our sample, state-level and market-level Republican vote shares are positively correlated but vary substantially, with $r = 0.27$.[9] Residents in more politically conservative areas have more discriminatory views toward transgender individuals in general (Prusaczyk and Hodson, 2020), which historical Republican vote shares capture.

Additionally, we use state-level measures of recently introduced and passed anti-transgender legislation based on the 180 days prior to application submission, relying on data from Trans Legislation Tracker (2025). The introduction of legislation may increase the salience of transgender rights, and hence employer awareness. Additionally, Roy et al. (2025) find that individuals in states with a greater number of anti-transgender laws are more likely to have negative attitudes toward transgender individuals explicitly and implicitly, although they measure this relationship without controlling for underlying state-level conservatism.

These two measures capture different but related factors that may be associated with differential discrimination. Conditional on Republican vote shares, there remains substantial heterogeneity in the introduction and passage of state-level anti-transgender laws. The correlation between market-level 2012–2020 Republican vote shares and anti-transgender laws across submissions in our sample is 0.20–0.25.

4 Results

Figure 1 shows mean callback rates by gender identity, with cisgender rates shown for applicants without pronouns. The callback rate is 14.5% for cisgender men and 13.8% for cisgender women. We see that callback rates for transgender women and non-binary ap-

[8] We pre-specified the 2020 Republican vote share as the primary political-climate measure. We use the 2012–2020 average because it smooths idiosyncratic election-to-election variation and may better reflect persistent local political preferences. However, results are nearly identical across all three definitions (Appendix Table A.5).

[9] We assign Craigslist markets to their corresponding county. For the four state-level markets, we assign the county that reflects the largest population center.

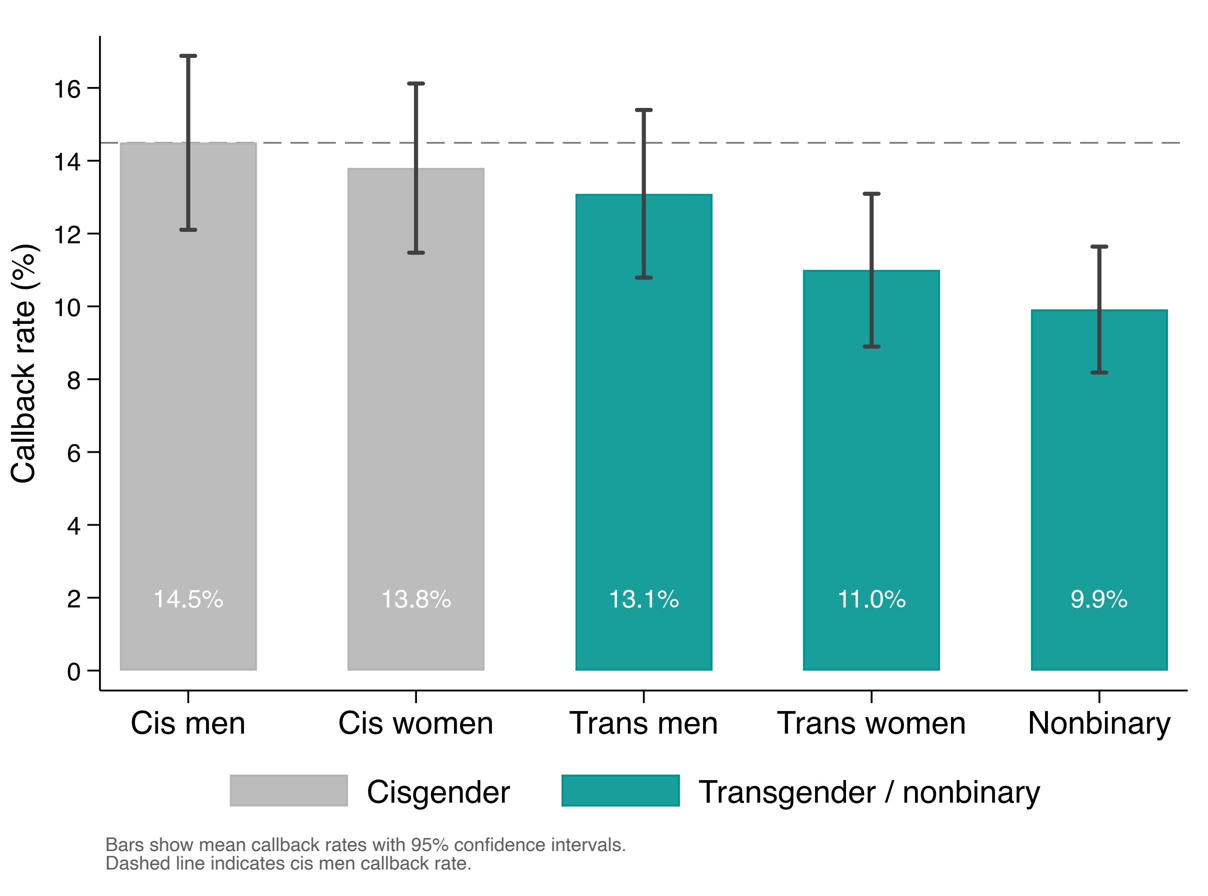

Figure 1: Callback rate by gender identity

plicants are substantially lower, at 11.0% and 9.9%, respectively. Regression estimates are shown in Table 2, which include pre-specified phase and market-level fixed effects, along with controls for customer-facing positions. Column 1 shows that transgender applicants have a 2.1 percentage point lower callback rate than cisgender applicants, which is statistically significant at the 5% level. Column 2 disaggregates transgender applicants into transgender men, transgender women, and non-binary applicants, and Column 3 includes an indicator for cisgender women, reflecting Equation 1, such that the omitted category is cisgender men. This disaggregation shows no evidence of discrimination against transgender men relative to cisgender applicants. However, we see evidence of more pronounced discrimination against transgender women (2.8 pp lower callback rate relative to cisgender applicants, significant at the 5% level) and non-binary applicants (2.4 pp lower callback rate relative to cisgender applicants, significant at the 5% level). The regression-adjusted non-binary gap is smaller than the raw gap in Figure 1 because non-binary profiles are included only in Phase 2, which had lower overall callback rates, and the phase and market fixed effects absorb this difference. After controlling for cisgender women in Column 3, such that the reference category is cisgender men, the transgender woman coefficient remains marginally significant at the 10% level, while the non-binary coefficient is no longer statistically significant. In both Columns 2 and 3, we fail to reject the null of zero discrimination across the three gender identity groups considered.

In aggregate, we see no evidence that gender or the inclusion of pronouns affects callback rates for cisgender applicants, consistent with meta-analytic evidence of limited aggregate gender bias in hiring for entry-level positions (Park and Oh, 2025). The coefficients for cisgender applicants that included pronouns are very close to zero, with a 95% confidence interval ranging from -2.7pp to 2.5pp.

As pre-specified, we also report Romano-Wolf stepdown adjusted p-values (Romano and Wolf, 2005) for the family of gender identity hypotheses, listed in the Table 2 footnote. The adjusted p-values are broadly consistent but more conservative than the unadjusted results:

with $p = 0.060$ for transgender women and $p = 0.101$ for non-binary applicants.

Appendix Table A.6 shows the robustness of our results to a range of controls. Results are also qualitatively similar when restricting to Phase 2 applications only (Appendix Table A.7).[10] Columns 7–10 of Appendix Table A.6 restrict to employers who received both a transgender and a cisgender application. Point estimates on this restricted sample are similar to the full sample (Columns 7–8), and the inclusion of employer fixed effects in Columns 9–10 strengthens the results. The penalty for transgender women rises to 4.7 percentage points ($p = 0.006$), confirming that discrimination operates within employers rather than through employer composition.

Table 3 shows that Black applicants are 3.1 percentage points less likely to receive a callback than White applicants, which is statistically significant at the 10% level. However, we do not find evidence that discrimination against transgender applicants varies differentially by race. The interaction term for being Black and Transgender is 1.0 percentage points and not statistically significant ($p = 0.59$). The disaggregated specifications in columns 2 and 3 also show no evidence of differential discrimination against transgender applicants by race. We also cannot reject that callback rates for cisgender applicants with pronouns differ by race, though we note that the non-binary signal differs slightly for White and Black applicants. White non-binary applicants received either gender-neutral or gendered names with they/them pronouns, while all Black non-binary applicants received gendered names with they/them pronouns. However, we do not find detectable differences in callback rates depending on whether non-binary applicant names are gendered, as Appendix Table A.2 shows.[11]

[10] In addition to only including White cisgender and transgender men and women, Phase 1 includes four markets and is conducted one year prior to Phase 2. Phase 1 applicants also have a college degree while Phase 2 applicants have a high school diploma. Appendix Tables A.8 and A.9 report the race-interaction and political-climate specifications restricted to Phase 2.

[11] One possible explanation for the absence of race differences in transgender discrimination is attention discrimination: employers with anti-Black preferences may reject applicants with a Black-signaling name—visible in the email address and body—without opening the resume and learning the applicant's gender identity (Bartoš et al., 2016). Future correspondence studies can address this design limitation by including identity signals in the email body rather than only in the resume (Tomlin, 2024).

Table 2: Impact of gender identity on callback rates

	(1)	(2)	(3)
Transgender	-0.021**		
	(0.010)		
Cis, with pronouns	-0.000	-0.001	-0.001
	(0.013)	(0.013)	(0.013)
Trans man		-0.011	-0.009
		(0.013)	(0.014)
Trans woman		-0.028**	-0.026*
		(0.012)	(0.014)
Nonbinary		-0.024**	-0.021
		(0.012)	(0.014)
Cis woman			0.005
			(0.012)
Observations	5623	5623	5623
Callback rate, cis men	0.145	0.145	0.145
Joint p: identity = 0	0.025	0.086	0.235
Pairwise p: TM = TW		0.238	0.238
Pairwise p: TM = NB		0.367	0.367

Sample includes Phase 1 and Phase 2 resumes. All specifications include market-level fixed effects and controls for customer-facing positions. Standard errors clustered at the employer level reported in parentheses. Joint p: identity = 0 is a joint test that all gender identity coefficients equal zero. Romano-Wolf stepdown adjusted p-values (1,000 bootstrap replications) for the family of gender identity hypotheses in Column 3: trans man $p = 0.564$, trans woman $p = 0.060$, non-binary $p = 0.101$.

Table 3: Impact of gender identity on callback rates, by race

	(1)	(2)	(3)
Transgender	-0.025**		
	(0.011)		
Black	-0.031*	-0.026	-0.029
	(0.016)	(0.023)	(0.024)
Black X transgender	0.010		
	(0.018)		
Trans man		-0.015	-0.018
		(0.015)	(0.017)
Trans woman		-0.025*	-0.028
		(0.015)	(0.017)
Nonbinary		-0.017	-0.021
		(0.017)	(0.019)
Cis, with pronouns		0.018	0.018
		(0.019)	(0.019)
Black X trans man		0.024	0.027
		(0.030)	(0.032)
Black X trans woman		0.002	0.005
		(0.028)	(0.030)
Black X non-binary		-0.002	0.002
		(0.027)	(0.029)
Black X cis pronouns		-0.039	-0.038
		(0.027)	(0.027)
Black X cis woman		0.024	0.031
		(0.019)	(0.024)
Cis woman			-0.007
			(0.016)
Observations	5623	5623	5623
Callback rate, cis men	0.145	0.145	0.145
Joint p: identity = 0	0.023	0.477	0.421
Joint p: race x identity = 0	0.588	0.825	0.806

Sample includes Phase 1 and Phase 2 resumes. All specifications include market-level fixed effects and controls for customer-facing positions. Standard errors clustered at the employer level reported in parentheses. Joint p: identity = 0 is a joint test that all gender identity coefficients equal zero. Joint p: race x identity = 0 tests that all race × gender identity interaction terms equal zero.

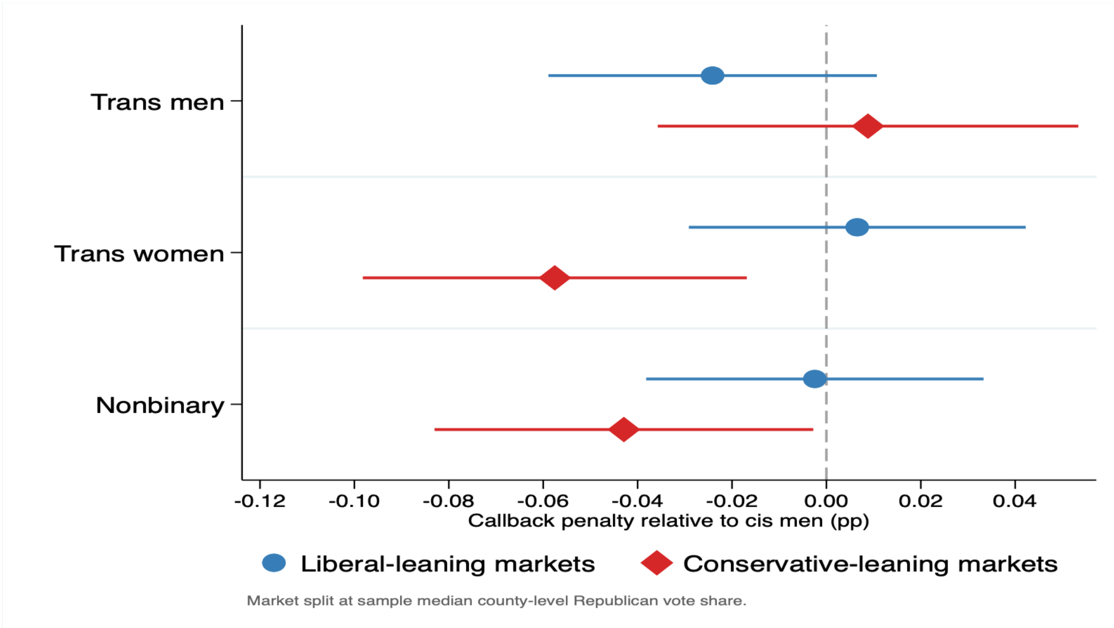

Figure 2: Callback penalty by gender identity and local political climate

4.1 Heterogeneity by political climate

To examine heterogeneity by political climates and attitudes toward transgender individuals across the United States, we interact gender identity with indicators for having a Republican vote share that was in the upper median of our sample (37%), averaging over the 2012–2020 presidential elections.[12] We use this historical average vote share to capture general political preferences that precede the broader rise in anti-transgender legislation beginning in 2021 and 2022 (Nagourney and Peters, 2023; Trans Legislation Tracker, 2025).[13] We necessarily exclude market-level fixed effects, so we control for county-level unemployment rate, racial composition, state LGBT population share, and state effective minimum wage.

Figure 2 shows stark evidence of discrimination against transgender women and non-binary applicants in markets with above-median Republican vote shares. Column 1 of Table 4 shows that the interaction term for transgender women is negative (–6.5pp) and statistically

[12]Appendix Figure A.2 plots the distribution of county-level Republican vote shares. Because the sample is restricted to markets with an active Craigslist market, which tends to be more urban, the vote share distribution is left-skewed, and "above-median Republican" markets are moderate by national standards.

[13]Trans Legislation Tracker (2025) documents that the number of introduced anti-transgender bills was doubled to 153 in 2021, with 175 in 2022 and 615 in 2023.

significant at the 1% level, and the interaction term for non-binary applications is negative (-4.1pp) and statistically significant at the 10% level. Interactions with cisgender women and cisgender applicants are negative and not statistically significant. When testing for discrimination against transgender applicants overall in high-Republican share states, we strongly reject the null, indicating the presence of discrimination against transgender applicants, with a p-value less than 0.001. Overall, the callback penalty in above-median Republican markets is 5.8 percentage points for transgender women and 4.4 percentage points for non-binary applicants.

In Columns 2 and 3, we consider heterogeneity by the passage of anti-transgender legislation (Trans Legislation Tracker, 2025). Column 2 uses a binary indicator for any bills *introduced* in the 180 days before application submission. In Column 3, we calculate the number of anti-transgender bills passed in the previous calendar year and include an indicator for being in the upper half of this distribution (mean of 0.33). Appendix Figure A.3 shows the distribution of anti-transgender legislation across states in our sample. The correlation between above-median Republican vote shares in Column 1 and these legislative variables is 0.13 and 0.11, respectively. In both legislation specifications, the transgender-identity interaction terms are smaller in magnitude than the voting share interaction terms and they are not statistically significant. We fail to reject the joint null of no discrimination against transgender applicants in above-median states in either specification ($p = 0.217$ for introduced bills and $p = 0.169$ for passed bills).[14][15]

We also estimate a specification that simultaneously includes interactions between gender identity and Republican vote share and recently introduced anti-transgender bills (Appendix Table A.12). The Republican vote share interactions remain jointly significant ($p = 0.005$

[14]Results are similar when we use continuous measures (Appendix Tables A.5 and A.10), although the policy X non-binary term is no longer statistically significant, and the policy X trans man term is large, positive, and statistically significant.

[15]Because anti-transgender legislation varies at the state level, we also estimate a version of Columns 2–3 of Table 4 that clusters standard errors at the state rather than market level (Appendix Table A.11). No qualitative conclusions change, and the ratio of state-clustered to market-clustered standard errors ranges from 0.78–1.10.

using median splits; $p < 0.001$ using continuous measures), and the legislation interactions are not jointly significant once vote share is controlled for ($p = 0.301$ using median splits; $p = 0.373$ using continuous measures), suggesting that underlying political conservatism rather than the legislative environment per se is more strongly associated with greater discrimination.

These results are robust to interacting gender identity with continuous measures of Republican vote share and anti-trans legislation and to defining election periods as 2020 only or the 2016–2020 average (Appendix Tables A.5 and A.10). Leave-one-market and leave-one-state checks confirm that the vote share heterogeneity results are not driven by any individual market or state (Appendix Figure A.4). Appendix Figure A.5 plots the market-level transgender callback gap against Republican vote share separately for transgender women and non-binary applicants, showing that the negative relationship is broad-based rather than driven by a few extreme markets.

4.2 Robustness checks

As specified in our pre-analysis plan, we also report a parsimonious version of the heterogeneity specifications without market-level demographic or economic controls; results are very similar (Appendix Table A.13).

One reason that our aggregate results may be more modest than previous studies (Campbell et al., 2025) is that the labor market in the 2023–24 study period was historically tight. The job-openings rate in the accommodation and food services sector, which comprises the majority of our sample, averaged 6.7%, well above its 2015–2019 mean of 5.3% (Bureau of Labor Statistics, 2025). We consider whether cross-market labor market tightness might affect patterns, as discrimination against some applicants becomes more costly for employers when labor markets are tighter (Becker, 1957; Baert et al., 2015; Modestino et al., 2020) and tightness could be correlated with our political attitude and policy variables. We interact gender identity with the one-month lagged county-level unemployment rate. Appendix Table

Table 4: Impact of gender identity on callback rates, policy heterogeneity (at median)

	(1)	(2)	(3)
	Rep. share (2012–20)	Any bills, 180d	Bills passed, 1yr lag
Trans man	-0.023	-0.011	-0.019
	(0.015)	(0.018)	(0.013)
Trans woman	0.007	-0.015	-0.023
	(0.019)	(0.016)	(0.015)
Nonbinary	-0.003	-0.018	-0.021
	(0.015)	(0.016)	(0.015)
Cis, with pronouns	0.006	0.006	0.002
	(0.018)	(0.017)	(0.017)
Cis woman	0.027**	0.028	0.012
	(0.012)	(0.018)	(0.017)
Policy X Trans man	0.031	0.003	0.038
	(0.023)	(0.027)	(0.029)
Policy X Trans woman	-0.065***	-0.026	-0.011
	(0.024)	(0.030)	(0.035)
Policy X Non-binary	-0.041*	-0.010	-0.003
	(0.023)	(0.022)	(0.028)
Policy X Cis (pronoun)	-0.021	-0.029	-0.014
	(0.026)	(0.028)	(0.025)
Policy X Cis woman	-0.040	-0.051**	-0.014
	(0.025)	(0.025)	(0.031)
Observations	5623	5623	5623
Callback rate, cis men	0.145	0.145	0.145
Policy var. median	0.366	0.000	0.000
Joint p: identity = 0	0.437	0.679	0.211
Joint p: trans interactions = 0	0.001	0.748	0.322
Joint p: above med. effect = 0	0.000	0.217	0.169
Joint p: equal effects above med.	0.000	0.327	0.092

Sample includes Phase 1 and Phase 2 resumes. All specifications include controls for customer-facing positions, a Phase 1 indicator and its interaction with the policy measure, county-level unemployment rate, county racial composition (share non-Hispanic White and Black, ACS), state-level LGBT population share (Williams Institute), and state effective minimum wage. Standard errors clustered at the market level reported in parentheses. Joint p: identity = 0 tests that all non-interacted gender identity coefficients equal zero. Joint p: trans interactions = 0 tests that the transgender-identity interaction terms jointly equal zero. Joint p: above med. effect = 0 tests that the summed effect (gender identity coefficient plus its interaction) equals zero for all three transgender identities. Joint p: equal effects above med. tests that the three summed effects are equal to one another.

A.14 shows no evidence that callback gaps by gender identity vary with local unemployment rates: the interaction terms are close to zero and individually and jointly insignificant across specifications.

We construct a sector-specific measure of labor demand by measuring year-over-year growth in the food-service and retail industries using the Quarterly Census of Employment and Wages, lagged one quarter, at the MSA level. We interact gender identity with this measure, separately and jointly with the unemployment rate, and report results in Appendix Table A.15. Interactions at the median are statistically insignificant. However, in continuous specifications, we find evidence that callback penalties for transgender women and non-binary applicants are in fact *larger* where employment growth is faster (jointly significant at the 10% level). Quartile binned estimates (Appendix Figure A.6) show that this reflects the absence of a hiring premium for cisgender men in the relatively small set of contracting markets, while callback rates for transgender and non-binary applicants are similar across the distribution.

We also pre-specified a test of whether discrimination is greater in customer-facing positions, consistent with a model in which employers discriminate based on perceived customer preferences (Holzer and Ihlanfeldt, 1998). We interact customer-facing status with gender identity indicators and do not find evidence of differential discrimination by customer-facing status (Appendix Table A.16), though we cannot rule out that employers apply perceived customer preferences uniformly across roles.[16]

5 Conclusions

We conduct a large-scale correspondence study across 48 markets in 27 states to test the impact of gender identity and race on employer demand. We then investigate the relation-

[16] Twenty-eight observations (15 unique postings) had ambiguous or missing customer-facing classifications. We hand-coded these from job titles and descriptions, reclassifying 9 observations as customer-facing and confirming 19 as non-customer-facing. Mixed-role postings (e.g., "front and back of house") were conservatively coded as non-customer-facing. An AI-assisted validation of the full sample yielded 85% agreement ($\kappa = 0.70$); see Appendix B.6.

ship of these impacts with local preferences and political climates, as proxied by 2012–2020 Republican presidential vote shares and the recent introduction or passage of state-level anti-transgender legislation.

Consistent with past literature, we find evidence of discrimination against transgender applicants overall, although the magnitude is smaller. One possibility for these more modest findings is that our study took place in 2023–2024, when the U.S. labor market was historically tight. If greater competition for workers reduces discrimination (Becker, 1957; Baert et al., 2015), then gaps measured in this period could be smaller than those measured in slacker markets. Additionally, we find that discrimination is highly correlated with local political environments. Transgender women and non-binary applicants in Republican-leaning labor markets are 4.4–5.8 percentage points less likely to receive a callback. Despite strong heterogeneity in the recent rise of state-level anti-transgender legislation, we do not find evidence that the introduction or passage of anti-transgender laws is associated with differential callback rates for transgender applicants.

The study design has a few notable limitations. In general, correspondence studies on hiring can only detect discrimination at the interview offer phase of the hiring process. While this typically provides a lower bound on the extent of discrimination, because transgender applicants could disclose later in the process, the impacts of doing so may differ if employers at that point have additional information that weighs more heavily.

Specific to our study, selected markets with sufficient posting activity tended to be from urban and metropolitan areas. We also limit the sample of job postings to entry-level positions in the food and retail industries. In addition, employers who recruit through Craigslist may differ from those hiring through centralized applicant-tracking platforms or franchise systems, likely overrepresenting smaller and less formalized establishments whose callback decisions rest with individual managers rather than standardized screening processes. Due to the national scale of the study, the results still hold external validity for these entry-level positions in urban and metropolitan labor markets in the United States. Future research on transgender and non-binary hiring discrimination could explore outcomes in rural labor markets and those not captured through Craigslist postings.

The absence of a relationship between anti-transgender legislation and discrimination against transgender job seekers could reflect several factors. Pre-existing social preferences may dominate employer callback decisions (Becker, 1957), employers may hold stable beliefs about transgender workers that new legislation does not shift (Bohren et al., 2019), or employers may already act in alignment with their own preferences, such that increased salience (or "permission") had no additional effect (Bursztyn et al., 2020). Alternatively, it could be that negative state-level policy climates could have an opposing effect on non-discriminatory employers, leading to no detectable impacts on average. Of course, gender identity could have been insufficiently salient or could have been difficult to interpret by some employers, which could have attenuated our estimates.

Taken together, these results highlight that employment discrimination varies substantially among transgender applicants depending on their gender identity, consistent with past literature. Additionally, we find that heterogeneity in political environments is an important predictor of the experience that transgender applicants have in the labor market. While anti-transgender legislation does not appear to exacerbate employment discrimination in the broad range of markets we consider, we find that underlying voter preferences are an important predictor.

Broadly, our findings suggest that political environments are associated with labor market discrimination less through ongoing policy debates and more through underlying social preferences. This relationship suggests that patterns of discrimination may be more stable across changing political climates, while longer-run shifts in societal attitudes toward transgender individuals may be more important for reducing labor market discrimination.

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A Appendix Figures and Tables

Figure A.1: Example resumes

(a) Example 1: Retail

Prince Booker (They/them)

St. Louis, MO • prince.booker811@yahoo.com • (816) 290-6291

PROFESSIONAL EXPERIENCE

WALMART SUPERCENTER, St. Louis, MO — *August 2021 - Present*
Retail Associate

- Greeted and assisted customers in a friendly and helpful manner.
- Provided product information, answered questions, and made personalized recommendations.
- Processed customer transactions using point-of-sale systems.
- Maintained a clean and organized sales floor, including restocking shelves and arranging displays.

WALGREENS, St. Louis, MO — *September 2018 - March 2020*
Warehouse Clerk

- Received, inspected, and recorded incoming shipments, verifying contents against packing lists and purchase orders.
- Maintained inventory storage, warehouse space, and performed regular cycle counts.
- Prepared and processed outgoing shipments, ensuring accurate labeling and documentation.

EDUCATION

Affton High School, Affton, MO — *May 2021*

(b) Example 2: Food service

Kenya Mosley

Baltimore, MD
(443) 342-9835
kenya.mosley916@yahoo.com

My preferred name is Kenya. My legal name is Reginald.

PROFESSIONAL EXPERIENCE

APPLEBEE'S GRILL + BAR, — **Baltimore, MD**
SERVER — *July 2021 - Present*

- Greeted and assisted customers in a friendly manner, providing menu recommendations and answering questions.
- Took customer orders, ensuring attention to special requests and dietary restrictions.
- Served food and beverages quickly, maintaining a high standard of quality and presentation.
- Collaborated with team members to ensure smooth service.

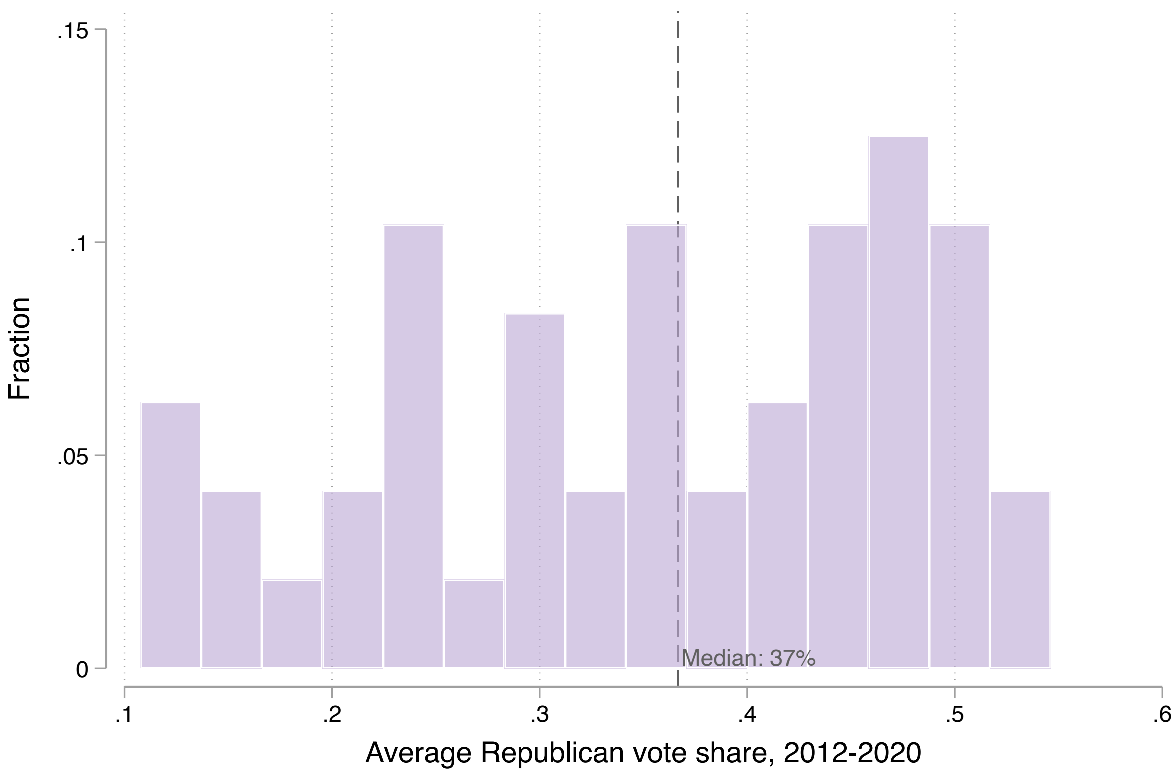
IHOP, — **Baltimore, MD**
LINE COOK — *August 2018 - March 2020*

- Sorted, scraped, and rinsed dishes, utensils, and kitchenware before loading them into the dishwasher.
- Operated and maintained commercial dishwashing equipment.
- Washed pots, pans, and cooking utensils by hand as needed.
- Followed health and safety standards and regulations.

EDUCATION

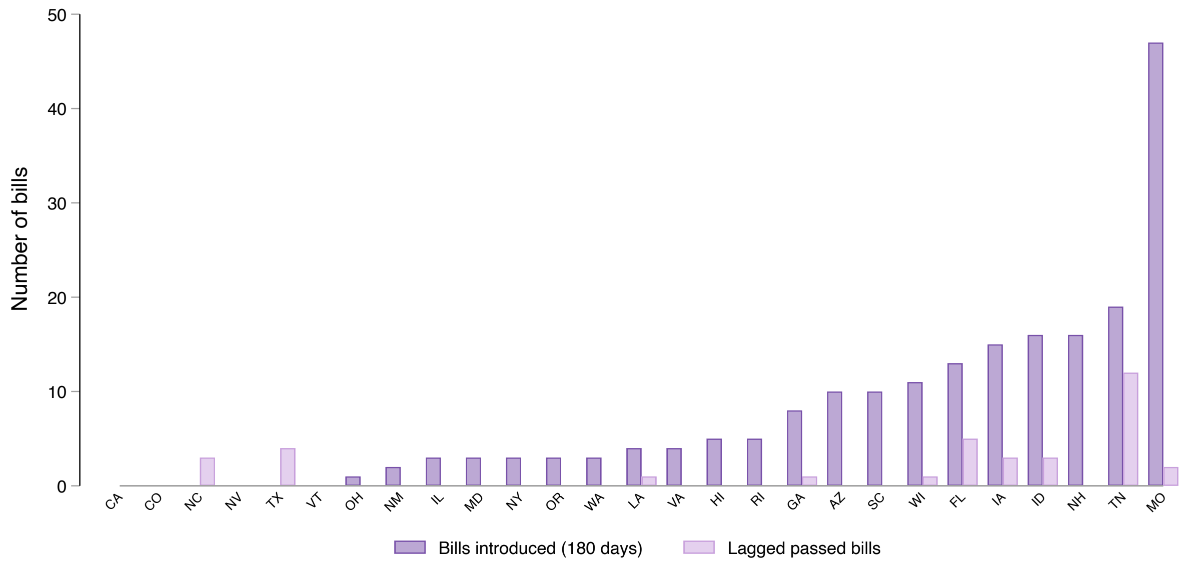
Coppin Academy — **Baltimore, MD**
May 2021

Figure A.2: Distribution of county-level Republican vote shares



Notes: Histogram of average Republican presidential vote shares (2012–2020) across counties in our sample, with one observation per county.

Figure A.3: Anti-transgender legislation by state



Notes: Number of anti-transgender bills introduced within 180 days of application submission and lagged passed anti-transgender bills, by state. Source: Trans Legislation Tracker (2025).

Table A.1: Robustness: excluding Mary Hansen applications

	(1)	(2)	(3)
Transgender	-0.021***		
	(0.008)		
Trans man		-0.010	-0.009
		(0.013)	(0.014)
Trans woman		-0.029**	-0.028*
		(0.013)	(0.014)
Nonbinary		-0.030**	-0.029**
		(0.013)	(0.014)
Cis, with pronouns		-0.005	-0.005
		(0.014)	(0.014)
Cis woman			0.002
			(0.013)
Observations	5117	5117	5117
Callback rate, cis men	0.145	0.145	0.145
Joint p: identity = 0	0.009	0.053	0.120
Pairwise p: TM = TW		0.224	0.225
Pairwise p: TM = NB		0.175	0.175

Robustness check excluding all applications using the name Mary Hansen, which was selected based on overall rather than recent name popularity. Sample includes Phase 1 and Phase 2 resumes. All specifications include market-level fixed effects and controls for customer-facing positions. Standard errors clustered at the employer level reported in parentheses. Joint p: identity = 0 is a joint test that all gender identity coefficients equal zero.

Table A.2: Impact of name gender on callback rates among non-binary applicants (PAP §4.1)

	(1)	(2)	(3)
	NB only: binary	NB only: 3-way	Full sample
Gender-neutral name	0.006	0.016	
	(0.022)	(0.024)	
Feminine name (among gendered)		0.021	
		(0.021)	
Trans man			-0.009
			(0.014)
Trans woman			-0.026*
			(0.014)
Nonbinary			-0.029*
			(0.017)
Cis, with pronouns			-0.001
			(0.013)
Cis woman			0.005
			(0.012)
Non-binary X neutral name			0.012
			(0.023)
Non-binary X feminine name			0.013
			(0.020)
Observations	1150	1150	5623
Callback rate, NB	0.099	0.099	
Callback rate, cis men			0.145
Joint p: identity = 0			0.190
Joint p: name effects			0.784
Pairwise p: neutral = feminine		0.851	

Columns 1–2 restrict to non-binary applicants; Column 3 uses the full sample. Gender-neutral names (Skyler Jensen, Peyton Meyer) are assigned only to white non-binary applicants; Black non-binary applicants all receive gendered names (PAP §2.5). Base category: masculine name in Columns 1–2; cisgender men without pronouns in Column 3. All specifications include market fixed effects and controls for customer-facing positions. Standard errors clustered at the employer level reported in parentheses.

Table A.3: Balance across treatment arms

	(1) Cis, no pronouns	(2) Cis, pronouns	(3) Trans, binary	(4) Trans, non-binary	F-test for balance F-stat	p-value
Black	0.342	0.500	0.333	0.491	0.235	[0.872]
	(0.012)	(0.015)	(0.012)	(0.015)		
Food service	0.750	0.805	0.742	0.795	0.281	[0.839]
	(0.011)	(0.012)	(0.011)	(0.012)		
Customer-facing	0.534	0.467	0.546	0.472	0.789	[0.500]
	(0.012)	(0.015)	(0.012)	(0.015)		
Observations	1,683	1,110	1,680	1,150		

F-tests condition on market and phase fixed effects to account for changes in experimental design between phases and the stratified randomization design. Phase 1 included only White applicants and did not include non-binary applicants. The food-service indicator is missing for 35 submissions; its means and F-test use available observations.

Table A.4: Randomization inference for primary gender identity effects

	Pooled RI p	Disaggregated RI p
Transgender	0.0116	
Trans man		0.3896
Trans woman		0.0244
Nonbinary		0.0384

Fisher randomization inference p-values (5,000 permutations of the gender identity treatment, stratified by market). Column 1 pools all transgender identities; Column 2 disaggregates into transgender men, transgender women, and non-binary applicants. Treatment-determined covariates (cisgender pronouns, cisgender woman) are omitted from the RI regressions; their coefficients are approximately zero in the main specifications.

Table A.5: Impact of gender identity on callback rates, heterogeneity by Republican vote shares

	Continuous Republican vote share			**Above median Republican vote share**		
	(1)	(2)	(3)	(4)	(5)	(6)
	2020	2016–2020	2012–2020	2020	2016–2020	2012–2020
Trans man	-0.065**	-0.063**	-0.066**	-0.028*	-0.022	-0.023
	(0.026)	(0.026)	(0.027)	(0.016)	(0.016)	(0.015)
Trans woman	0.044	0.039	0.041	0.007	0.007	0.007
	(0.029)	(0.029)	(0.030)	(0.019)	(0.019)	(0.019)
Nonbinary	-0.010	-0.009	-0.003	-0.002	0.000	-0.003
	(0.031)	(0.031)	(0.032)	(0.015)	(0.015)	(0.015)
Cis, with pronouns	-0.004	-0.007	-0.004	0.000	0.000	0.006
	(0.039)	(0.037)	(0.038)	(0.017)	(0.017)	(0.018)
Cis woman	0.059*	0.056*	0.060*	0.026**	0.030**	0.027**
	(0.032)	(0.032)	(0.033)	(0.012)	(0.012)	(0.012)
Rep. vote X Trans man	0.173**	0.169**	0.172**			
	(0.075)	(0.076)	(0.076)			
Rep. vote X Trans woman	-0.207**	-0.196**	-0.194**			
	(0.081)	(0.080)	(0.080)			
Rep. vote X Non-binary	-0.035	-0.039	-0.054			
	(0.094)	(0.096)	(0.097)			
Rep. vote X Cis (pronoun)	0.005	0.014	0.005			
	(0.108)	(0.107)	(0.105)			
Rep. vote X Cis woman	-0.154	-0.148	-0.153			
	(0.105)	(0.106)	(0.108)			
Rep. vote, p50 X Trans man				0.042*	0.030	0.031
				(0.022)	(0.023)	(0.023)
Rep. vote, p50 X Trans woman				-0.065**	-0.065***	-0.065***
				(0.024)	(0.024)	(0.024)
Rep. vote, p50 X Non-binary				-0.043*	-0.045*	-0.041*
				(0.023)	(0.023)	(0.023)
Rep. vote, p50 X Cis (pronoun)				-0.008	-0.007	-0.021
				(0.026)	(0.026)	(0.026)
Rep. vote, p50 X Cis woman				-0.040	-0.047*	-0.040
				(0.025)	(0.024)	(0.025)
Observations	5623	5623	5623	5623	5623	5623
Callback rate, cis men	0.145	0.145	0.145	0.145	0.145	0.145
Interact var. mean	0.337	0.332	0.344	0.482	0.488	0.482
Joint p: identity = 0	0.011	0.014	0.009	0.315	0.438	0.437
Joint p: trans interactions = 0	0.000	0.000	0.000	0.000	0.001	0.001
Joint p: above med. effect = 0				0.000	0.000	0.000
Joint p: equal effects above med.				0.000	0.000	0.000

Sample includes Phase 1 and Phase 2 resumes. All specifications include controls for customer-facing positions, a Phase 1 indicator and its interaction with the policy measure, county-level unemployment rate, county racial composition (share non-Hispanic White and Black, ACS), state-level LGBT population share (Williams Institute), and state effective minimum wage. Standard errors clustered at the market level reported in parentheses. Joint p: identity = 0 tests that all non-interacted gender identity coefficients equal zero. Joint p: trans interactions = 0 tests that the transgender-identity interaction terms jointly equal zero. Joint p: above med. effect = 0 tests that the summed effect (gender identity coefficient plus its interaction) equals zero for all three transgender identities. Joint p: equal effects above med. tests that the three summed effects are equal to one another. Gender identity indicators interacted with county-level presidential Republican vote shares averaged over the indicated election years.

Table A.6: Robustness: Impact of gender identity on callback rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Transgender	-0.023**		-0.021**		-0.021**		-0.018*		-0.026**	
	(0.010)		(0.010)		(0.010)		(0.011)		(0.011)	
Cis, with pronouns	-0.002	-0.003	-0.000	-0.001	0.002	0.001	0.007	0.005	-0.018	-0.022
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.017)	(0.017)	(0.018)	(0.018)
Trans man		-0.007		-0.009		-0.009		-0.003		0.005
		(0.014)		(0.014)		(0.014)		(0.017)		(0.017)
Trans woman		-0.027*		-0.026*		-0.025*		-0.031**		-0.047***
		(0.014)		(0.014)		(0.014)		(0.016)		(0.017)
Nonbinary		-0.022		-0.021		-0.019		-0.030*		-0.035*
		(0.014)		(0.014)		(0.014)		(0.017)		(0.018)
Cis woman		0.008		0.005		0.006		-0.006		0.003
		(0.012)		(0.012)		(0.012)		(0.015)		(0.016)
Observations	5623	5623	5623	5623	5622	5622	3718	3718	3718	3718
Market FE			X	X	X	X	X	X		
RA, Time FE					X	X				
Employer FE									X	X
Callback rate, cis men	0.145	0.145	0.145	0.145	0.145	0.145	0.153	0.153	0.153	0.153
Joint p: identity = 0	0.018	0.188	0.025	0.235	0.027	0.288	0.095	0.119	0.016	0.007
Pairwise p: TM = TW		0.175		0.238		0.277		0.107		0.004
Pairwise p: TM = NB		0.277		0.367		0.461		0.161		0.051

Sample includes Phase 1 and Phase 2 resumes. Odd-numbered columns pool all transgender identities; even-numbered columns disaggregate by identity. Pooled specifications control for cisgender pronouns; disaggregated specifications additionally control for cisgender women. *RA and Time FE* include year-week, day-of-week, and submitter fixed effects. All specifications include controls for customer-facing positions and a binary indicator for project phase. Columns 7–10 restrict to employers who received both a transgender and a cisgender application. Standard errors clustered at the employer level in parentheses.

Table A.7: Impact of gender identity on callback rates (Phase 2 only)

	(1)	(2)	(3)
Transgender	-0.021**		
	(0.009)		
Trans man		-0.018	-0.010
		(0.016)	(0.018)
Trans woman		-0.021	-0.014
		(0.016)	(0.017)
Nonbinary		-0.024*	-0.017
		(0.013)	(0.015)
Cis, with pronouns		-0.001	-0.001
		(0.014)	(0.014)
Cis woman			0.014
			(0.014)
Observations	4523	4523	4523
Callback rate, cis men	0.123	0.123	0.123
Joint p: identity = 0	0.018	0.279	0.705
Pairwise p: TM = TW		0.867	0.866
Pairwise p: TM = NB		0.668	0.667

Sample restricted to Phase 2 resumes only. All specifications include market-level fixed effects and controls for customer-facing positions. Standard errors clustered at the employer level reported in parentheses. Joint p: identity = 0 is a joint test that all gender identity coefficients equal zero.

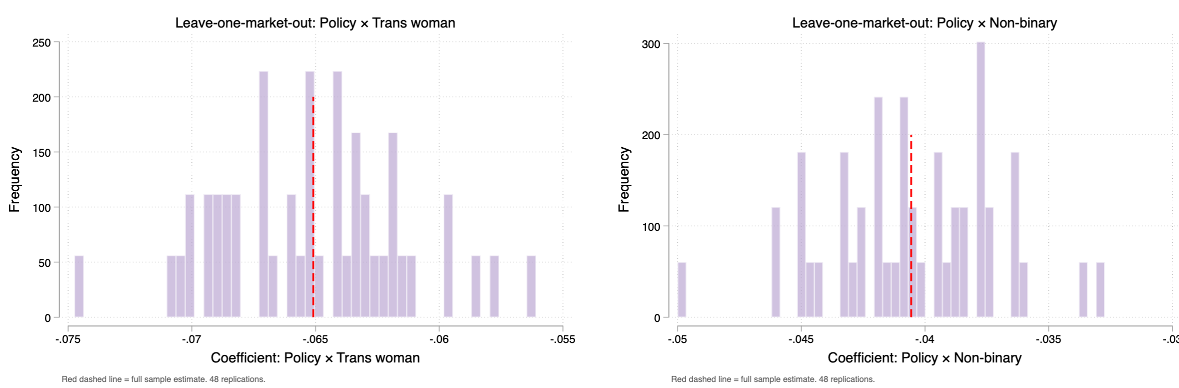


Figure A.4: Leave-one-market-out coefficient distributions for the vote share heterogeneity specification (Table 4, Column 1). Red dashed line indicates the full-sample estimate.

Table A.8: Impact of gender identity on callback rates, by race (Phase 2 only)

	(1)	(2)	(3)
Transgender	-0.028**		
	(0.014)		
Black	-0.029*	-0.022	-0.019
	(0.017)	(0.024)	(0.026)
Black X transgender	0.013		
	(0.020)		
Trans man		-0.030	-0.027
		(0.022)	(0.024)
Trans woman		-0.008	-0.005
		(0.023)	(0.025)
Nonbinary		-0.017	-0.015
		(0.019)	(0.022)
Cis, with pronouns		0.019	0.020
		(0.020)	(0.020)
Black X trans man		0.038	0.035
		(0.034)	(0.036)
Black X trans woman		-0.013	-0.016
		(0.033)	(0.035)
Black X non-binary		-0.002	-0.005
		(0.028)	(0.030)
Black X cis pronouns		-0.042	-0.042
		(0.028)	(0.028)
Black X cis woman		0.025	0.019
		(0.019)	(0.027)
Cis woman			0.006
			(0.021)
Observations	4523	4523	4523
Callback rate, cis men	0.123	0.123	0.123
Joint p: identity = 0	0.050	0.619	0.698
Joint p: race x identity = 0	0.509	0.508	0.512

Sample restricted to Phase 2 resumes only. All specifications include market-level fixed effects and controls for customer-facing positions. Standard errors clustered at the employer level reported in parentheses. Joint p: identity = 0 is a joint test that all gender identity coefficients equal zero. Joint p: race x identity = 0 tests that all race × gender identity interaction terms equal zero.

Table A.9: Impact of gender identity on callback rates, policy heterogeneity at median (Phase 2 only)

	(1)	(2)	(3)
	Rep. share (2012–20)	Any bills, 180d	Bills passed, 1yr lag
Trans man	-0.031	-0.008	-0.026
	(0.021)	(0.022)	(0.018)
Trans woman	0.017	-0.020	-0.018
	(0.025)	(0.018)	(0.019)
Nonbinary	-0.002	-0.019	-0.019
	(0.016)	(0.017)	(0.015)
Cis, with pronouns	0.006	0.005	-0.001
	(0.019)	(0.018)	(0.018)
Cis woman	0.028*	0.029	0.022
	(0.015)	(0.020)	(0.018)
Policy X Trans man	0.045	-0.006	0.046
	(0.033)	(0.040)	(0.038)
Policy X Trans woman	-0.061*	0.012	0.009
	(0.032)	(0.039)	(0.037)
Policy X Non-binary	-0.031	0.002	0.005
	(0.025)	(0.025)	(0.029)
Policy X Cis (pronoun)	-0.021	-0.025	-0.005
	(0.028)	(0.032)	(0.026)
Policy X Cis woman	-0.022	-0.035	-0.015
	(0.030)	(0.027)	(0.032)
Observations	4523	4523	4523
Callback rate, cis men	0.123	0.123	0.123
Policy var. median	0.366	0.000	0.000
Joint p: identity = 0	0.268	0.612	0.409
Joint p: trans interactions = 0	0.005	0.969	0.556
Joint p: above med. effect = 0	0.003	0.857	0.461
Joint p: equal effects above med.	0.008	0.961	0.335

Sample restricted to Phase 2 resumes only. All specifications include controls for customer-facing positions, county-level unemployment rate, county racial composition (share non-Hispanic White and Black, ACS), state-level LGBT population share (Williams Institute), and state effective minimum wage. Standard errors clustered at the market level reported in parentheses. Joint p: identity = 0 tests that all non-interacted gender identity coefficients equal zero. Joint p: trans interactions = 0 tests that the transgender-identity interaction terms jointly equal zero. Joint p: above med. effect = 0 tests that the summed effect (gender identity coefficient plus its interaction) equals zero for all three transgender identities. Joint p: equal effects above med. tests that the three summed effects are equal to one another.

Table A.10: Impact of gender identity on callback rates, heterogeneity by anti-trans legislation

	Continuous anti-trans legislation				**Above median anti-trans legislation**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bills, 180d	Any bills, 180d	Lag bills, CY	Lag passed bills, CY	Bills, 180d	Any bills, 180d	Lag bills, CY	Lag passed bills, CY
Trans man	-0.017	-0.011	-0.018	-0.014	-0.011	-0.011	-0.017	-0.019
	(0.015)	(0.018)	(0.014)	(0.012)	(0.018)	(0.018)	(0.014)	(0.013)
Trans woman	-0.018	-0.015	-0.028*	-0.021	-0.015	-0.015	-0.021	-0.023
	(0.015)	(0.016)	(0.016)	(0.014)	(0.016)	(0.016)	(0.014)	(0.015)
Nonbinary	-0.021	-0.018	-0.021	-0.029**	-0.018	-0.018	-0.018	-0.021
	(0.013)	(0.016)	(0.015)	(0.014)	(0.016)	(0.016)	(0.018)	(0.015)
Cis, with pronouns	-0.006	0.006	0.004	0.003	0.006	0.006	0.006	0.002
	(0.015)	(0.017)	(0.016)	(0.015)	(0.017)	(0.017)	(0.021)	(0.017)
Cis woman	0.012	0.028	0.004	0.010	0.028	0.028	0.020	0.012
	(0.014)	(0.018)	(0.017)	(0.015)	(0.018)	(0.018)	(0.021)	(0.017)
Anti-trans legis X Trans man	0.001	0.003	0.001	0.005				
	(0.002)	(0.027)	(0.001)	(0.005)				
Anti-trans legis X Trans woman	-0.001	-0.026	0.000	-0.005				
	(0.001)	(0.030)	(0.001)	(0.006)				
Anti-trans legis X Non-binary	-0.000	-0.010	-0.000	0.006				
	(0.002)	(0.022)	(0.001)	(0.008)				
Anti-trans legis X Cis (pronoun)	0.001	-0.029	-0.001	-0.005				
	(0.002)	(0.028)	(0.001)	(0.004)				
Anti-trans legis X Cis woman	-0.001	-0.051**	0.000	-0.002				
	(0.002)	(0.025)	(0.001)	(0.006)				
Anti-trans legis, p50 X Trans man					0.003	0.003	0.021	0.038
					(0.027)	(0.027)	(0.024)	(0.029)
Anti-trans legis, p50 X Trans woman					-0.026	-0.026	-0.010	-0.011
					(0.030)	(0.030)	(0.030)	(0.035)
Anti-trans legis, p50 X Non-binary					-0.010	-0.010	-0.008	-0.003
					(0.022)	(0.022)	(0.025)	(0.028)
Anti-trans legis, p50 X Cis (pronoun)					-0.029	-0.029	-0.017	-0.014
					(0.028)	(0.028)	(0.026)	(0.025)
Anti-trans legis, p50 X Cis woman					-0.051**	-0.051**	-0.027	-0.014
					(0.025)	(0.025)	(0.029)	(0.031)
Observations	5623	5623	5623	5623	5623	5623	5623	5623
Callback rate, cis men	0.145	0.145	0.145	0.145	0.145	0.145	0.145	0.145
Interact var. mean	4.436	0.419	10.530	1.168	0.419	0.419	0.500	0.330
Joint p: identity = 0	0.409	0.679	0.302	0.172	0.679	0.679	0.362	0.211
Joint p: trans interactions = 0	0.078	0.748	0.196	0.083	0.748	0.748	0.654	0.322
Joint p: above med. effect = 0					0.217	0.217	0.283	0.169
Joint p: equal effects above med.					0.327	0.327	0.258	0.092

Sample includes Phase 1 and Phase 2 resumes. All specifications include controls for customer-facing positions, a Phase 1 indicator and its interaction with the policy measure, county-level unemployment rate, county racial composition (share non-Hispanic White and Black, ACS), state-level LGBT population share (Williams Institute), and state effective minimum wage. Standard errors clustered at the market level reported in parentheses. Joint p: identity = 0 tests that all non-interacted gender identity coefficients equal zero. Joint p: trans interactions = 0 tests that the transgender-identity interaction terms jointly equal zero. Joint p: above med. effect = 0 tests that the summed effect (gender identity coefficient plus its interaction) equals zero for all three transgender identities. Joint p: equal effects above med. tests that the three summed effects are equal to one another.

Table A.11: Legislation heterogeneity: state-level clustering

	Any bills, 180d		**Bills passed, 1yr lag**	
	(1)	(2)	(3)	(4)
	Market cl.	State cl.	Market cl.	State cl.
Trans man	-0.011	-0.011	-0.019	-0.019
	(0.018)	(0.014)	(0.013)	(0.012)
Trans woman	-0.015	-0.015	-0.023	-0.023
	(0.016)	(0.016)	(0.015)	(0.016)
Nonbinary	-0.018	-0.018	-0.021	-0.021
	(0.016)	(0.016)	(0.015)	(0.016)
Cis, with pronouns	0.006	0.006	0.002	0.002
	(0.017)	(0.017)	(0.017)	(0.016)
Cis woman	0.028	0.028*	0.012	0.012
	(0.018)	(0.016)	(0.017)	(0.016)
Policy X Trans man	0.003	0.003	0.038	0.038
	(0.027)	(0.021)	(0.029)	(0.027)
Policy X Trans woman	-0.026	-0.026	-0.011	-0.011
	(0.030)	(0.031)	(0.035)	(0.036)
Policy X Non-binary	-0.010	-0.010	-0.003	-0.003
	(0.022)	(0.018)	(0.028)	(0.025)
Policy X Cis (pronoun)	-0.029	-0.029	-0.014	-0.014
	(0.028)	(0.024)	(0.025)	(0.027)
Policy X Cis woman	-0.051**	-0.051**	-0.014	-0.014
	(0.025)	(0.022)	(0.031)	(0.029)
Observations	5623	5623	5623	5623
Callback rate, cis men	0.145	0.145	0.145	0.145
Policy var. median	0.000	0.000	0.000	0.000
Joint p: identity = 0	0.679	0.669	0.211	0.211
Joint p: trans interactions = 0	0.748	0.763	0.322	0.382
Joint p: above med. effect = 0	0.217	0.244	0.169	0.187
Joint p: equal effects above med.	0.327	0.360	0.092	0.105

Robustness check clustering standard errors at the state level (27 clusters) rather than the market level (48 clusters). Because anti-transgender legislation varies at the state level, state-level clustering may be more appropriate for the legislation specifications. Sample includes Phase 1 and Phase 2 resumes. All specifications include controls for customer-facing positions, a Phase 1 indicator and its interaction with the policy measure, county-level unemployment rate, county racial composition (share non-Hispanic White and Black, ACS), state-level LGBT population share (Williams Institute), and state effective minimum wage. Joint p: identity = 0 tests that all non-interacted gender identity coefficients equal zero. Joint p: trans interactions = 0 tests that the transgender-identity interaction terms jointly equal zero. Joint p: above med. effect = 0 tests that the summed effect (gender identity coefficient plus its interaction) equals zero for all three transgender identities. Joint p: equal effects above med. tests that the three summed effects are equal to one another.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: Heterogeneity by political climate and legislation

	(1) Above median	(2) Continuous
Trans man	-0.020	-0.062**
	(0.017)	(0.027)
Trans woman	0.012	0.040
	(0.016)	(0.030)
Nonbinary	-0.001	-0.002
	(0.017)	(0.033)
Cis, with pronouns	0.016	-0.005
	(0.022)	(0.038)
Cis woman	0.042***	0.060*
	(0.015)	(0.036)
Rep. vote × Trans man	0.031	0.149*
	(0.026)	(0.087)
Rep. vote × Trans woman	-0.063**	-0.180*
	(0.028)	(0.093)
Rep. vote × Non-binary	-0.038	-0.055
	(0.024)	(0.099)
Legislation × Trans man	-0.007	0.001
	(0.031)	(0.002)
Legislation × Trans woman	-0.015	-0.001
	(0.031)	(0.001)
Legislation × Non-binary	-0.007	-0.000
	(0.024)	(0.002)
Rep. vote × Cis (pronoun)	-0.022	-0.002
	(0.026)	(0.100)
Rep. vote × Cis woman	-0.034	-0.144
	(0.026)	(0.125)
Legislation × Cis (pronoun)	-0.029	0.001
	(0.029)	(0.002)
Legislation × Cis woman	-0.046*	-0.001
	(0.026)	(0.002)
Observations	5623	5623
Callback rate, cis men	0.145	0.145
Joint p: identity = 0	0.413	0.013
Joint p: vote share het.	0.005	0.000
Joint p: bills het.	0.301	0.373
R^2	0.033	0.032

Sample includes Phase 1 and Phase 2 resumes. All specifications include controls for customer-facing positions, a Phase 1 indicator, county-level unemployment rate, county racial composition (share non-Hispanic White and Black, ACS), state-level LGBT population share (Williams Institute), and state effective minimum wage. Standard errors clustered at the market level in parentheses. Column 1 uses above-median binary splits; Column 2 uses continuous measures. Both policy dimensions (Republican vote share 2012–2020 and anti-trans bills introduced within 180 days) entered simultaneously.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.13: Impact of gender identity on callback rates, policy heterogeneity (at median), no market controls

	(1)	(2)	(3)
	Rep. share (2012–20)	Any bills, 180d	Bills passed, 1yr lag
Trans man	-0.020	-0.008	-0.019
	(0.015)	(0.018)	(0.012)
Trans woman	0.004	-0.016	-0.022
	(0.018)	(0.016)	(0.014)
Nonbinary	-0.003	-0.018	-0.021
	(0.015)	(0.015)	(0.015)
Cis, with pronouns	0.006	0.007	0.002
	(0.018)	(0.017)	(0.018)
Cis woman	0.027**	0.029	0.013
	(0.012)	(0.018)	(0.017)
Policy X Trans man	0.029	0.001	0.040
	(0.023)	(0.027)	(0.029)
Policy X Trans woman	-0.063**	-0.026	-0.014
	(0.024)	(0.029)	(0.033)
Policy X Non-binary	-0.041*	-0.010	-0.002
	(0.023)	(0.023)	(0.028)
Policy X Cis (pronoun)	-0.019	-0.030	-0.014
	(0.026)	(0.029)	(0.025)
Policy X Cis woman	-0.041	-0.052*	-0.014
	(0.025)	(0.026)	(0.031)
Observations	5623	5623	5623
Callback rate, cis men	0.145	0.145	0.145
Interact var. mean	0.482	0.419	0.330
Joint p: identity = 0	0.533	0.659	0.199
Joint p: trans interactions = 0	0.001	0.758	0.247
Joint p: above med. effect = 0	0.000	0.200	0.111
Joint p: equal effects above med.	0.000	0.271	0.057

Sample includes Phase 1 and Phase 2 resumes. Parsimonious specification per pre-analysis plan: no market-level demographic or economic controls. All specifications include controls for customer-facing positions and a Phase 1 binary indicator. Standard errors clustered at the market level reported in parentheses. Joint p: identity = 0 tests that all non-interacted gender identity coefficients equal zero. Joint p: trans interactions = 0 tests that the transgender-identity interaction terms jointly equal zero. Joint p: above med. effect = 0 tests that the summed effect (gender identity coefficient plus its interaction) equals zero for all three transgender identities. Joint p: equal effects above med. tests that the three summed effects are equal to one another.

Table A.14: Impact of gender identity on callback rates, heterogeneity by local unemployment rate

	Continuous		**Above median**	
	(1)	(2)	(3)	(4)
	Unemp. (state)	Unemp. (county)	Unemp. (state)	Unemp. (county)
Trans man	-0.054	-0.020	-0.021	-0.010
	(0.047)	(0.070)	(0.018)	(0.019)
Trans woman	-0.035	0.008	-0.028	-0.024
	(0.065)	(0.090)	(0.023)	(0.021)
Nonbinary	-0.066	-0.114*	-0.030*	-0.041**
	(0.045)	(0.059)	(0.016)	(0.017)
Cis, with pronouns	0.022	0.058	-0.007	-0.008
	(0.067)	(0.074)	(0.017)	(0.018)
Cis woman	0.015	-0.014	0.009	0.016
	(0.042)	(0.056)	(0.015)	(0.016)
Unemp. × Trans man	1.158	0.003	0.025	0.003
	(1.056)	(0.017)	(0.022)	(0.024)
Unemp. × Trans woman	0.213	-0.009	0.003	-0.005
	(1.497)	(0.022)	(0.029)	(0.028)
Unemp. × Non-binary	1.123	0.024	0.017	0.039
	(1.095)	(0.015)	(0.020)	(0.026)
Unemp. × Cis (pronoun)	-0.683	-0.016	0.006	0.010
	(1.700)	(0.018)	(0.024)	(0.028)
Unemp. × Cis woman	-0.204	0.005	-0.004	-0.021
	(1.112)	(0.015)	(0.023)	(0.030)
Observations	5623	5623	5623	5623
Callback rate, cis men	0.145	0.145	0.145	0.145
Interact var. mean	0.039	3.910	0.487	0.460
Joint p: identity = 0	0.326	0.247	0.166	0.132
Joint p: trans interactions = 0	0.562	0.327	0.654	0.415
Joint p: above med. effect = 0			0.429	0.369
Joint p: equal effects above med.			0.341	0.302

Sample includes Phase 1 and Phase 2 resumes. All specifications include controls for customer-facing positions, a Phase 1 indicator and its interaction with the policy measure, county-level unemployment rate, county racial composition (share non-Hispanic White and Black, ACS), state-level LGBT population share (Williams Institute), and state effective minimum wage. Standard errors clustered at the market level reported in parentheses. Joint p: identity = 0 tests that all non-interacted gender identity coefficients equal zero. Joint p: trans interactions = 0 tests that the transgender-identity interaction terms jointly equal zero. Joint p: above med. effect = 0 tests that the summed effect (gender identity coefficient plus its interaction) equals zero for all three transgender identities. Joint p: equal effects above med. tests that the three summed effects are equal to one another.

Table A.15: Heterogeneity by labor market tightness: employment growth vs unemployment

	Continuous			**Above median**		
	(1) Growth	(2) Unemp.	(3) Both	(4) Growth	(5) Unemp.	(6) Both
Trans man	-0.002	-0.053	-0.048	0.005	-0.020	-0.006
	(0.014)	(0.047)	(0.047)	(0.018)	(0.018)	(0.019)
Trans woman	-0.015	-0.035	-0.028	-0.022	-0.028	-0.023
	(0.016)	(0.065)	(0.064)	(0.022)	(0.023)	(0.027)
Nonbinary	-0.014	-0.066	-0.058	-0.010	-0.030*	-0.017
	(0.014)	(0.045)	(0.047)	(0.018)	(0.016)	(0.020)
Cis, with pronouns	0.001	0.022	0.031	0.009	-0.008	0.008
	(0.015)	(0.067)	(0.068)	(0.020)	(0.017)	(0.023)
Cis woman	0.019	0.015	0.027	0.021	0.010	0.023
	(0.015)	(0.042)	(0.045)	(0.019)	(0.015)	(0.019)
Emp. growth × Trans man	-0.511		-0.540	-0.026		-0.033
	(0.391)		(0.391)	(0.023)		(0.024)
Emp. growth × Trans woman	-0.852**		-0.865**	-0.010		-0.013
	(0.413)		(0.414)	(0.025)		(0.025)
Emp. growth × Non-binary	-0.762*		-0.725*	-0.028		-0.028
	(0.431)		(0.418)	(0.025)		(0.025)
Emp. growth × Cis (pronoun)	-0.527		-0.614	-0.030		-0.034
	(0.412)		(0.448)	(0.026)		(0.026)
Emp. growth × Cis woman	-1.063		-1.057	-0.028		-0.029
	(0.726)		(0.737)	(0.025)		(0.026)
Unemp. × Trans man		1.137	1.172		0.024	0.029
		(1.058)	(1.078)		(0.022)	(0.024)
Unemp. × Trans woman		0.213	0.314		0.004	0.006
		(1.497)	(1.501)		(0.028)	(0.028)
Unemp. × Non-binary		1.124	1.128		0.016	0.017
		(1.095)	(1.152)		(0.020)	(0.020)
Unemp. × Cis (pronoun)		-0.682	-0.796		0.008	0.004
		(1.700)	(1.689)		(0.024)	(0.023)
Unemp. × Cis woman		-0.204	-0.219		-0.005	-0.003
		(1.112)	(1.156)		(0.023)	(0.023)
Observations	5622	5622	5622	5622	5622	5622
Callback rate, cis men	0.145	0.145	0.145	0.145	0.145	0.145
Joint p: growth X trans = 0	0.087		0.089	0.593		0.530
Joint p: unemp. X trans = 0		0.571	0.582		0.668	0.605

Sample includes Phase 1 and Phase 2 resumes with non-missing employment growth (QCEW food-services and retail combined year-over-year employment growth, lagged one quarter, MSA-level with state fill). Unemp. is the county-level unemployment rate. All specifications include controls for customer-facing positions, a Phase 1 indicator and its interaction with each interacted measure, county racial composition (share non-Hispanic White and Black, ACS), state-level LGBT population share (Williams Institute), and state effective minimum wage; the unemployment-rate level is included in every column. Columns 1–3 use continuous measures; Columns 4–6 use above-median indicators. Standard errors clustered at the market level in parentheses. Joint p rows test that the three transgender-identity interactions with the indicated measure jointly equal zero.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.16: Impact of gender identity on callback rates, by customer-facing status (PAP H4)

	(1)	(2)	(3)
Transgender	-0.027**		
	(0.012)		
Customer-facing	-0.018	-0.016	-0.024
	(0.014)	(0.023)	(0.025)
CF X Trans	0.012		
	(0.016)		
Trans man		-0.003	-0.014
		(0.022)	(0.025)
Trans woman		-0.033	-0.035
		(0.020)	(0.024)
Nonbinary		-0.032	-0.030
		(0.020)	(0.025)
Cis, with pronouns		0.007	0.026
		(0.019)	(0.024)
Cis woman		0.001	-0.011
		(0.019)	(0.022)
CF X Trans man		-0.010	-0.007
		(0.029)	(0.029)
CF X Trans woman		0.013	0.012
		(0.027)	(0.028)
CF X Non-binary		0.021	0.019
		(0.028)	(0.028)
CF X Cis (pronoun)		-0.016	-0.017
		(0.027)	(0.027)
CF X Cis woman		0.008	0.009
		(0.025)	(0.025)
Observations	5623	5623	5623
Callback rate, cis men	0.145	0.145	0.145
Joint p: identity = 0		0.249	0.485
Joint p: CF x identity = 0	0.464	0.735	0.808
Pairwise p: TM = TW		0.191	0.415
Pairwise p: TM = NB		0.182	0.528

Sample includes Phase 1 and Phase 2 resumes. All specifications include market-level fixed effects. Specification 3 includes race controls and race × identity interactions. Standard errors clustered at the employer level reported in parentheses. Joint p: identity = 0 is a joint test that all gender identity coefficients equal zero. Joint p: CF x identity = 0 tests that all customer-facing × gender identity interaction terms equal zero.

Table A.17: Impact of gender identity on callback rates: callback measurement robustness

	(1)	(2)	(3)	(4)
	All callbacks	All P1 + email P2	All callbacks	All P1 + email P2
Trans man	-0.009	-0.004	-0.023	-0.012
	(0.014)	(0.013)	(0.015)	(0.014)
Trans woman	-0.026*	-0.017	0.007	0.009
	(0.014)	(0.012)	(0.019)	(0.015)
Nonbinary	-0.021	-0.020*	-0.003	-0.000
	(0.014)	(0.012)	(0.015)	(0.013)
Cis, with pronouns	-0.001	0.001	0.006	0.011
	(0.013)	(0.011)	(0.018)	(0.015)
Cis woman	0.005	0.000	0.027**	0.020
	(0.012)	(0.011)	(0.012)	(0.012)
Policy X Trans man			0.031	0.019
			(0.023)	(0.022)
Policy X Trans woman			-0.065***	-0.050**
			(0.024)	(0.023)
Policy X Non-binary			-0.041*	-0.041*
			(0.023)	(0.022)
Policy X Cis (pronoun)			-0.021	-0.024
			(0.026)	(0.022)
Policy X Cis woman			-0.040	-0.038*
			(0.025)	(0.021)
Observations	5623	5623	5623	5623
Callback rate, cis men	0.145	0.117	0.145	0.117
Joint p: identity = 0	0.235	0.283	0.437	0.762
Joint p: interactions = 0			0.001	0.019

Column 1 uses all callbacks (email, text, and phone); Column 2 uses all Phase 1 callbacks plus email-only Phase 2 callbacks, as the phone number used in Phase 2 did not match the applicant name. Columns 3–4 repeat with above-median Republican vote share interactions and market-level controls. Standard errors clustered at the employer level (Columns 1–2) or market level (Columns 3–4) in parentheses.

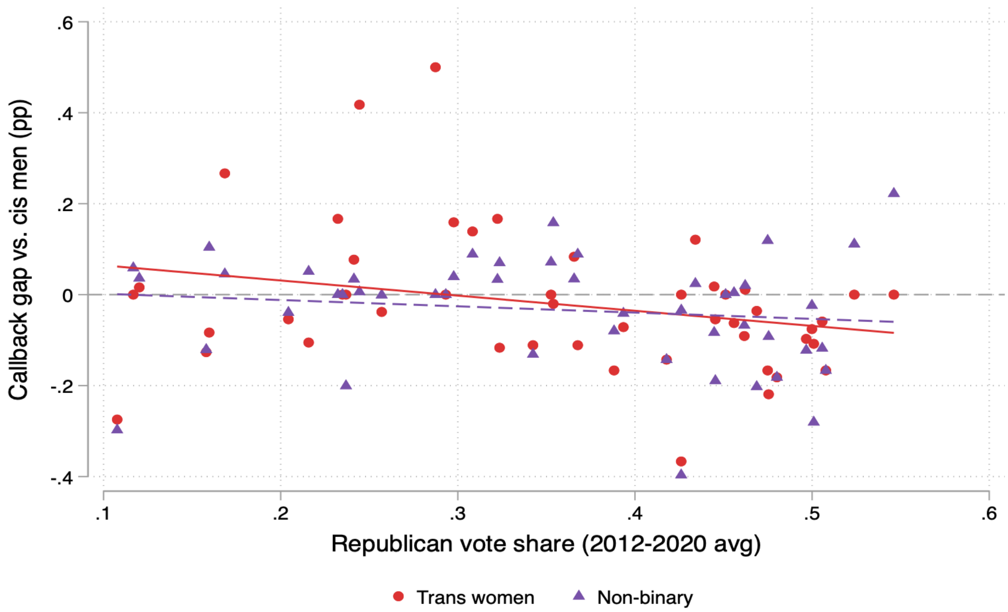


Figure A.5: Market-level callback gap (relative to cisgender men) versus Republican vote share (2012–2020 county average), separately for transgender women and non-binary applicants.

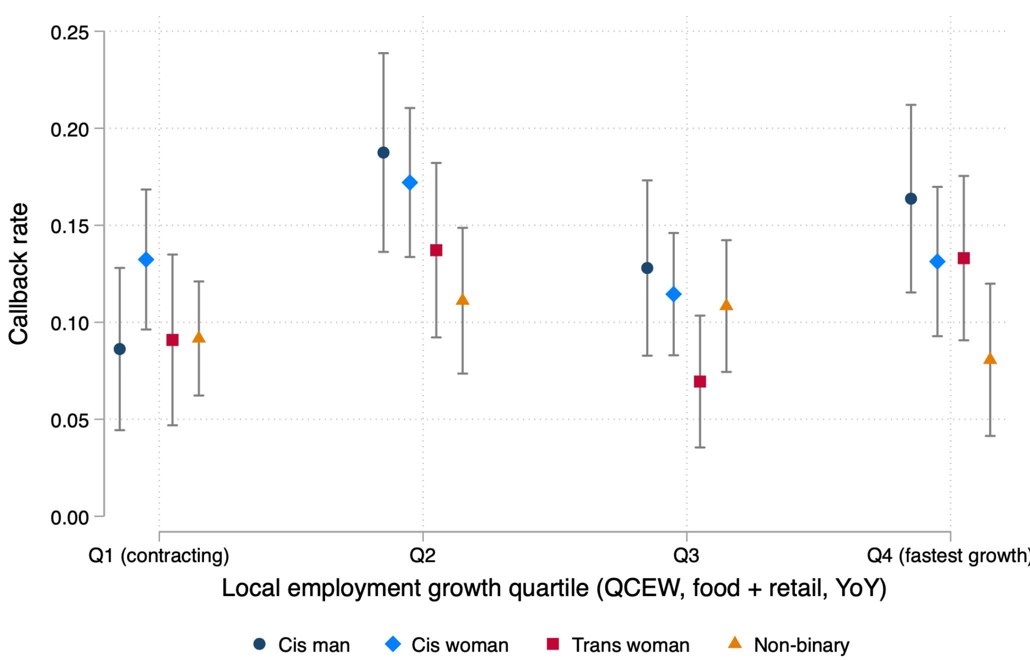
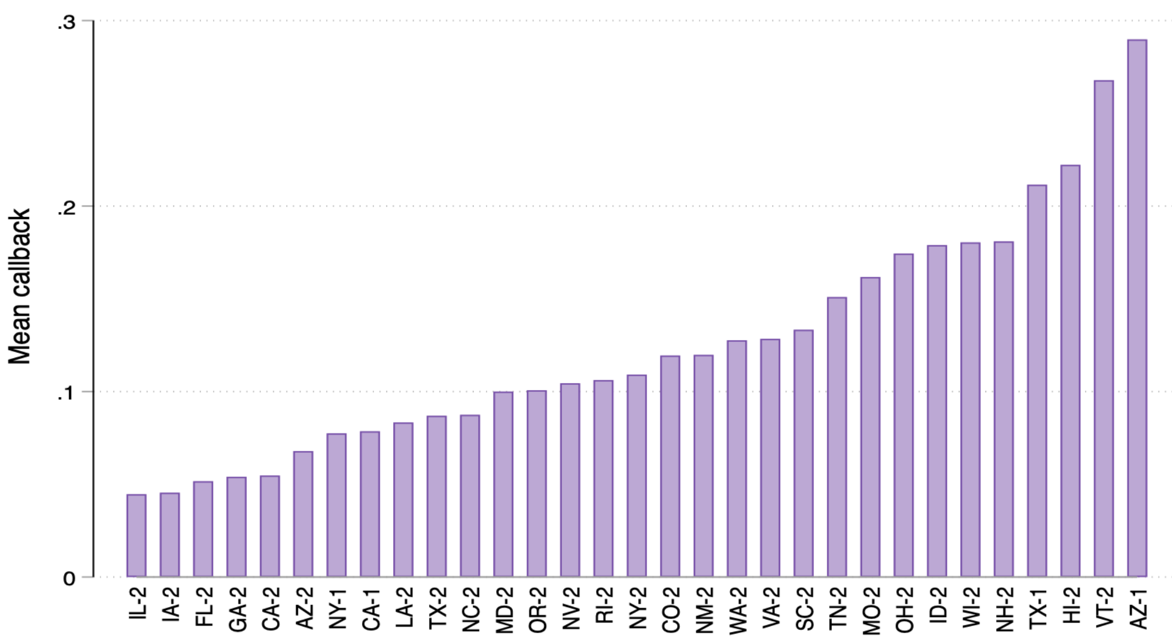


Figure A.6: Callback rates by gender identity and local employment growth quartile (QCEW food-service and retail combined employment, year-over-year, lagged one quarter). Bars show 95% confidence intervals.

Figure A.7: Callbacks by state and phase



B Implementation

We included 48 markets across 27 U.S. states, listed in Table B.1. We identified markets and states via the following procedure:

1. To identify sufficiently active markets, we counted the number of job postings with unique employers over a two-day period (August 21 and 22, 2023) within food-service positions, one of our two main industries, for each of 417 Craigslist markets in the United States.

2. We excluded any market with fewer than 5 postings during that period, leaving 110 markets across 40 states. We automatically included the four Phase 1 states: Arizona, California, New York, and Texas.

3. We merged the state-level Republican vote share from the 2020 presidential election (MIT Election Data and Science Lab, 2017) for the remaining 36 states. We randomly selected two-thirds of states (24), stratifying by Republican vote-share quartile (Table B.2), for a total of 28 states with 90 markets.

4. We selected the 4 Phase 1 markets and then up to two markets per state, with the state-specific probability of selection proportional to the number of job postings in that market. This yielded a total of 48 markets in 27 states.

5. We revised the list of markets to (1) ensure we did not include overlapping markets and (2) exclude markets that we later found had insufficient postings to be viable. We then revised selection to include up to three markets per state to compensate for the additional loss of markets.

This led to a final sample of 48 markets in 27 states. Revision details are described below.

B.0.1 Market selection revisions

We made the following revisions to our initial market selection:

- We dropped Miami and Long Island because Miami is equivalent to South Florida and Long Island is nested inside NYC.
- Upon second review in late November 2023, we identified 9 selected markets with 0–5 usable postings (excluding postings for DoorDash drivers, for example) in the food service sector for the entire month of November. We removed these markets and replaced them with the next selected market if one was available.
- We revised selection to include the top three randomly selected markets, excluding those dropped above.

B.0.2 Additional market notes

Four selected markets (Hawaii, New Hampshire, Rhode Island, and Vermont) cover job postings for their entire respective states. For each of these markets, we selected the city with the highest population for the applicants' backgrounds (location of high schools and work experience) and where they apply. The cities with the highest populations are Honolulu, HI; Manchester, NH; Providence, RI; and Burlington, VT.

We also note that two pairs of selected markets are close to one another (about a one-hour drive). These pairs are Annapolis and Baltimore, MD, and Madison and Milwaukee, WI. If one market in a pair has a shortage of job postings, it could draw upon postings from the other nearby market, so we made sure to check that the location of the postings is in the actual market and check for duplicate postings across markets.

B.1 Resume generation

B.1.1 Phase 1:

Each resume was tailored to the food or retail industry, and each applicant had two entry-level job experiences in each industry (one customer-facing, one non-customer-facing). Job descriptions were generated based on online resume samples and then edited appropriately.

The jobs and companies were standardized. Food industry positions included server and line cook, and the retail jobs were variants of retail associate and inventory assistant. The companies were selected from the highest-grossing chain restaurants and retailers in the United States. The chain restaurants were required to have a sit-down option so that job applicants could have been a server at said restaurants. Then, the locations of these jobs were selected from the companies' locations nearest the applicants' university.

The educational background included a high school degree and a four-year bachelor's degree, of which the latter was earned in the month of May previous to the submission of job applications to indicate that the job applicant was a recent graduate. Because the location of the university was not necessarily in close proximity to the job markets, the most recent job experience was in the location of the university from which the applicant graduated. The quality of both the diploma and the degree was standardized across resumes and states, with the high school and university located within the same state where the applicant submitted job applications.

B.1.2 Phase 2:

Each resume was tailored to the food or retail industry, and each applicant had two entry-level job experiences in each industry (one customer-facing, one non-customer-facing). Job descriptions were generated using ChatGPT and then edited appropriately.

The jobs and companies were standardized. Food industry positions included server and line cook, and the retail jobs were variants of retail associate and inventory assistant. The companies were selected from the highest-grossing chain restaurants and retailers in the United States. The chain restaurants were required to have a sit-down option so that job applicants could have been a server at said restaurants. Then, the locations of these jobs were selected from the companies' locations nearest the applicants' cities of residence.

Each resume had a high school degree from the high school located within their city of residence, and we targeted high schools that were ranked as "average" (5–6) by GreatSchools, extending the range to 4–7 when necessary. We included both public and charter high schools, excluding magnet schools.

B.2 Posting identification

We applied for entry-level food service and retail positions. Specifically, we targeted all postings listed on the food service and retail pages of the Craigslist job ads, excluding those that are (1) not entry-level (ex: manager positions that require more experience); (2) require the applicant to call, text, complete an application, write a cover letter, or go in-person to apply (3) and/or mass positions for gig positions through firms like DoorDash and InstaCart, which require applications via an external website.

Each week, we used a Python script to scrape food and retail job postings from all selected markets on Craigslist. The script removed ineligible postings, and we manually removed any ineligible postings that the code did not remove. In addition, we removed any posts from employers to whom we previously submitted job applications to avoid suspicion of the authenticity of the applications. If employers posted multiple positions, we randomly selected one position to apply to. Then, we divided the job postings into groups by market and sent them to the research assistants.

B.3 Name selection

We signaled applicant gender and race by selecting names that are particularly common to White women, Black women, White men, and Black men, using the SSA list of first names given to newborns in 2003 and 2000 U.S. Census data on surnames.

We identified gender-specific first names as those that are given to only girls or only boys at least 90% of the time. We identified White-signaling names as those given to White babies at least 90% of the time, and we identified Black-signaling names as those given to Black babies at least 50% of the time. Because many White names met these criteria, we restricted to names that were at least in the top 50 most popular names. Within the pool of potential names, we randomly selected two for each gender-race category.

We selected surnames that are at least 90 percent White or at least 40 percent Black. While many first and last names are at least 90 percent White, few are above 40 percent Black, which is why the cutoff percentage is lower for Black first and last names.

We signaled transgender identity by including a statement near the top of each resume stating that the applicant's preferred and legal names differ. For example, "My preferred name is Kenya, but my legal name is Reginald." One name was unambiguously masculine, while the other name was unambiguously feminine to establish a contrast in gender between the applicant's legal name and preferred name that signals transgender identity. We used the same set of names for legal names and preferred names.

B.4 Resume submissions

After randomizing the resumes and filling in the appropriate information, research assistants submitted applications to Craigslist. First, they copied a unique email address for the job posting on Craigslist and pasted it into the "to" field on the appropriate Yahoo email account. Second, they copied and pasted the email subject line (which varies to indicate gender identity internally) and added the job title. Third, they copied and pasted the email template and edited it to include the job title in the body of the email and the applicant's name in the email signature. Fourth, they attached the resume to the email and sent it to the employer.

B.5 Classifying callbacks

The nature of our experimental design required hand-coding to link employers to submissions in Phase 2. Because employers who responded by e-mail simply replied to the initial e-mail message, we can accurately link e-mail callbacks to submissions. Phone submissions were more challenging, as some employers left incomplete information. Through manual matching and verification, we were able to link 72% of phone callbacks to submissions. Because email is the most common contact method, the maximum mismatch rate is 11%, although it would be lower if employers reached out by phone and email. In the matched sample, 32% of applicants who were contacted by phone were also contacted by e-mail. If the same rate applies, then we miss approximately 7.5% of callbacks.[17] We also note that callback mode does not differ systematically by gender identity.[18]

B.6 Customer-facing classification

We classify each job posting as customer-facing or not based on whether the role's primary function involves directly serving, assisting, or interacting with customers, following Holzer and Ihlanfeldt (1998). Positions such as servers, cashiers, bartenders, hosts, retail sales associates, bussers, food runners, and other front-of-house staff are classified as customer-facing, since these workers are visible to and interact with customers in ways relevant to the taste-based discrimination mechanism. Back-of-house roles where workers do not regularly interact with customers (e.g., line cooks, dishwashers, janitors, warehouse workers, maintenance staff) are classified as not customer-facing, consistent with the functional distinction drawn in the *Dictionary of Occupational Titles* (U.S. Department of Labor, 1991) and the keyword-based approach in Nunley et al. (2015). Postings listing multiple roles, some customer-facing and some not (e.g., "Cashier and Cook"), are coded as customer-facing. Research assistants coded this variable during data collection; cases where the RA recorded the value as ambiguous or left it blank were hand-coded from the job title and description, with ambiguous cases conservatively coded as not customer-facing.

To validate the RA coding, we independently classified all job postings using an LLM (Claude Haiku), providing the job title, employer name, and job description as inputs.[19] The LLM classified each posting into one of four categories: customer-facing, not customer-

[17] Calculations conducted with any callbacks, not restricting to the two-week window.

[18] Appendix Table A.17 shows the robustness of our results to including only Phase 1 callbacks (which do not have this phone matching issue) plus e-mail only Phase 2 callbacks.

[19] Approximately 40% of Phase 2 observations and all Phase 1 observations lack job descriptions, in which case only the job title and employer name were provided.

facing, mixed (multiple roles), or ambiguous (insufficient information). Mapping mixed to customer-facing and ambiguous to not customer-facing, the overall agreement rate between the RA and LLM classifications was 85.0% (Cohen's $\kappa = 0.70$, $N = 6{,}230$). Restricting to definitive LLM classifications (i.e., excluding cases where the LLM returned mixed or ambiguous), agreement was 90.8% ($\kappa = 0.82$).[20] The validation identified a small number of systematic coding errors (e.g., merchandiser roles miscoded as customer-facing), which were reviewed by the research team and corrected.

[20]Agreement rates are similar across phases: 85.1% ($\kappa = 0.70$) for Phase 2 ($N = 5{,}130$) and 84.4% ($\kappa = 0.67$) for Phase 1 ($N = 1{,}100$). Phase 1 agreement is slightly lower because only job titles were available for classification, with no job descriptions.

Table B.1: Selected Markets

Phoenix	AZ	Phase 1
Tucson	AZ	Phase 2
Los Angeles	CA	Phase 1
Orange County	CA	Top-up
San Francisco Bay Area	CA	Phase 2
Boulder	CO	Phase 2
Denver	CO	Phase 2
High Rockies	CO	Top-up
South Florida	FL	Phase 2
Tampa Bay Area	FL	Phase 2
Atlanta	GA	Phase 2
Hawaii	HI	Phase 2
Iowa City	IA	Phase 2
Boise	ID	Phase 2
Chicago	IL	Phase 2
New Orleans	LA	Phase 2
Annapolis	MD	Phase 2
Baltimore	MD	Phase 2
Kansas City	MO	Phase 2
St Louis	MO	Phase 2
Charlotte	NC	Top-up
Raleigh / Durham / Ch	NC	Phase 2
Wilmington	NC	Phase 2
New Hampshire	NH	Phase 2
Albuquerque	NM	Phase 2
Santa Fe / Taos	NM	Phase 2
Las Vegas	NV	Phase 2
Reno / Tahoe	NV	Phase 2
Glens Falls	NY	Top-up
Hudson Valley	NY	Phase 2
New York City	NY	Phase 1
Cleveland	OH	Phase 2
Bend	OR	Top-up
Medford-Ashland	OR	Phase 2
Salem	OR	Phase 2
Rhode Island	RI	Phase 2
Charleston	SC	Phase 2
Nashville	TN	Phase 2
Dallas / Fort Worth	TX	Top-up
Houston	TX	Phase 1
San Antonio	TX	Phase 2
Richmond	VA	Phase 2
Vermont	VT	Phase 2
Seattle-Tacoma	WA	Phase 2
Spokane / Coeur D'Alene	WA	Phase 2
Wenatchee	WA	Top-up
Madison	WI	Phase 2
Milwaukee	WI	Phase 2
Total states	27	
Total markets	48	

Table B.2: Distribution of 2020 Republican vote shares

Vote-share quartile	Mean	p50	Min	Max
Quartile 1	0.323	0.34	0.054	0.404
Quartile 2	0.437	0.436	0.406	0.477
Quartile 3	0.505	0.499	0.478	0.533
Quartile 4	0.595	0.585	0.551	0.654
Total	0.462	0.478	0.054	0.654
Phase 1	0.432	0.433	0.343	0.521

Source: MIT Election Data and Science Lab (2017).

Table B.3: Applicant names

Panel A: Phase 1 (White applicants only)		
Female	Hannah Johnson	
	Madison Smith	
Male	Christopher Brown	
	Jacob Jones	
Legal names (transgender applicants)		
Female	Emily	
Male	Andrew	
Panel B: Phase 2		
	White	**Black**
Female	Katelyn Walsh	Ebony Dorsey
	Mary Hansen	Kenya Mosley
Male	Justin Carlson	Demetrius Banks
	Hunter Weber	Prince Booker
Gender ambiguous	Skyler Jensen	
	Peyton Meyer	
Legal names (transgender applicants)		
Female	Brooke	Aisha
	Nicole	Ayanna
Male	Thomas	Jermaine
	Gavin	Reginald