Multiracial Politicians and Political Representation: An Experimental Study*

Isaiah C. Johnson†

January 25, 2026

Draft: Do not Circulate Without Author's Consent

Abstract

Can Multiracial politicians accurately infer Black constituency preferences? I argue that racial competence, or the ability to identify Black communities' policy priorities, depends on contextual knowledge acquired through sustained socialization in Black environments. Because Multiracial Americans are disproportionately raised in racially mixed or majority-White contexts, they may lack the experiential foundation to translate demographic information into accurate policy inferences. I test this using an experiment where Black-White Multiracial and Black Monoracial respondents play incumbent politicians, matching policy positions to district preferences on community policing. Multiracial respondents outperform Monoracial respondents when preferences are directly observable. However, when preferences must be inferred from demographic cues alone, Multiracial respondents show a significant learning disadvantage that widens across repeated decisions. The mechanism is socialization rather than psychological identification: Multiracial respondents with greater exposure to Black social contexts perform significantly better, while politicized racial identity shows no moderating effect. These findings demonstrate that shared racial identity does not guarantee racial competence.

∗. The author would like to thank the members of The Lab on Politics, Race and Experimental Methods. I appreciate the mentorship of Ismail White, LaFleur Stephens-Dougan, and Gleason Judd in crafting this manuscript.

†. PhD Candidate in Politics, Princeton University. ij1791@princeton.edu.

Introduction

"It's not color, it's culture," said Denzel Washington in a 2016 Sirius XM Urban View interview about the significance of Black film having Black directors. Washington went on to claim that it was not about racial identity per se but cultural knowledge – the ability to know the "smell of a hot comb on a Sunday morning" – that enables Black directors to accurately depict Black life in America.[1] This quote embodies the arguments made for descriptive representation in the political sphere: by electing leaders with shared experiences, Black voters gain assurances that their unique circumstances will be represented (Dovi 2002; Mansbridge 1999; Wamble 2025). However, not every descriptive representative is equipped with the contextual knowledge necessary to substantively represent Black voters. Multiracial politicians, who often lack forms of contextual knowledge by not having experienced Black social networks and institutions (Rockquemore 1999; Rockquemore and Brunsma 2002), may be ill-prepared to address the particular needs of Black constituencies.[2]

There are significant examples of Multiracials being positioned as uniquely racially competent across both Black and White racial contexts (Lemi 2021; Velasquez-Manoff 2017). Much of the discussion surrounding President Obama's Multiracialism centered on whether his background would lend him an increased ability to deliver policy goals to both Black and White Americans (Walters 2007). Moreover, one of the central criticisms of Vice President Harris from President Trump involved questioning her Biracial heritage (Fowler 2024). Yet, this framing assumes that Multiracial politicians possess the contextual knowledge necessary to navigate multiple racial contexts, an assumption that has not been empirically tested.

This paper asks: Do Multiracial individuals possess the contextual knowledge necessary to correctly infer Black constituency preferences? And if deficits exist, what explains them? I argue that racial competence, or the ability to correctly identify and act on the policy priorities of Black communities, depends on contextual knowledge acquired through sustained socialization in Black environments. Because Americans who self-identify as Multiracial are disproportionately raised in racially mixed or majority-White contexts (Rockquemore 1999; Rockquemore and Brunsma 2002), they are less likely to have developed the experiential foundation necessary to translate demographic information into accurate policy inferences.

I test this argument using an original experiment in which Black-White Multiracial and Black Monoracial respondents play a repeated game as incumbent politicians seeking reelection. Respondents must match their policy position to district preferences on community policing as well as Medicare and abortion rights, which serve as placebo issues. By randomly assigning respondents to conditions in which district preferences are either directly revealed or inferred from demographic composition, I can isolate whether Multiracials exhibit deficits specifically when racial competence is required.

1. For the full interview, see "Denzel Washington: 'It's Not Color, It's Culture,'" uploaded by Sirius XM, December 20, 2016, https://www.youtube.com/watch?v=9Ayf8Iny9Eg.

2. For the purposes of this paper, I define Multiracial as an individual who identifies as being part-Black and part-White. I utilize the terms Multiracial, Biracial, and mixed-race interchangeably.

I find that Multiracial respondents perform as well as or better than Monoracial respondents when constituency preferences are directly observable. However, when preferences must be inferred solely from demographic cues, Multiracial respondents exhibit a significant learning disadvantage that widens across repeated decisions. This deficit emerges specifically for community policing but not for Medicare or abortion, consistent with the domain-specificity of racial competence. Critically, the mechanism is socialization rather than psychological identification: Multiracial respondents with greater exposure to Black social contexts perform significantly better, while politicized racial identity shows no moderating effect.

This paper makes three contributions. First, it advances theories of descriptive representation by demonstrating that shared racial identity does not guarantee racial competence. Competence must be acquired through socialization, and representatives who lack such socialization may struggle to infer constituent preferences in particularized domains. Second, it contributes to the growing literature on Multiracial politics by providing the first experimental evidence that Multiracials face systematic disadvantages in correctly identifying Black constituency preferences. Prior work has focused on how voters evaluate Multiracial candidates (Lemi 2021; Leslie et al. 2022); this paper shifts attention to the politicians themselves (though see Lemi (2017, 2026)). Third, it provides an empirical test of the formal model developed in Johnson (2026), which predicts that Multiracial incumbents will struggle in particularized policy domains due to deficits in racial competency.

The paper proceeds as follows. I first develop a theory linking racial competence to contextual knowledge and explain why Multiracial politicians may lack this capacity. I then describe the experimental design, present results from the main analyses and mechanism tests, and conclude with implications for descriptive representation and Multiracial politics.

Theory

Descriptive Representation and Racial Competency

Theories of descriptive representation argue that shared racial identity provides Black voters with assurance that their interests will be substantively represented in the policymaking process (Mansbridge 1999). While descriptive representation may not always be necessary or sufficient for achieving substantive outcomes (Pitkin 1967; Swain 1995; Young 1997, 2002), a large body of empirical work demonstrates that electing coracial officeholders yields meaningful benefits for Black communities. Descriptive representation improves constituent-legislator relations on the voter side through empowerment (Banducci, Donovan, and Karp 2004; Bobo and Gilliam Jr 1990; Clark 2019; Gleason and Stout 2014), efficacy (Bowen and Clark 2014; Merolla, Sellers, and Fowler 2013; West 2017), and trust (Williams 1993). Moreover, coracial politicians produce more Black-oriented legislation for their communities, impacting the constituent-legislator relationship institutionally.[3]

3. For a review, see Stout, Tate, and Wilson (2021).

A substantial body of research demonstrates that descriptive representation yields substantive benefits for Black constituents through multiple legislative channels, including roll-call voting (Grose 2005; Tate 2003; Whitby 2000), committee participation (Ellis and Wilson 2013; Gamble 2007; Minta 2011), and agenda-setting (Orey 2000; Whitby 2000). While this literature establishes that coracial legislators deliver for their constituents, it largely assumes that shared racial identity reliably signals the capacity to do so. Less understood is how legislators acquire the contextual knowledge necessary to identify and act on constituent preferences – a question that becomes especially pressing for representatives whose racial identity does not straightforwardly signal group membership.

I define racial competence as the ability of representatives to credibly understand, articulate, and advance the policy priorities of Black communities, a capacity grounded in "strong mutual relationships with dispossessed sub-groups" (Dovi 2002, 735). This capacity is not automatic; it must be signaled through legislative behavior, communication styles, and public rhetoric (Harris-Lacewell 2010; Walters 2007; Wamble 2025). Such signals are treated as observable cues that allow voters to infer whether an elected official embodies the lived experiences and commitments associated with Black political life.

Recent work challenges the assumption that competence can be read directly from racial identity. Wamble (2025) shows that Black voters will support White politicians whose behavior signals racial competence, suggesting that competence must be inferred from observable actions rather than assumed from descriptive identity. This finding raises a deeper challenge: what happens when descriptive identity itself is ambiguous?

The Challenge of Multiracial Politicians

Multiracial politicians complicate the assumption that racial identity conveys competency due to their ambiguous identity. Specifically, voters face uncertainty about whether Multiracial politicians possess the lived experiences and contextual knowledge necessary to identify and act on Black constituency preferences. Lemi (2021) finds that mixed-race politicians are perceived as capable of building interracial coalitions but at the expense of in-group authenticity, a tradeoff driven by voters' difficulty placing ambiguous candidates within familiar racial categories. Leslie et al. (2022) show that Monoracial voters rely on perceived racial heritage rather than a candidate's chosen identity when forming competency judgments, further illustrating how ambiguity disrupts the heuristic value of race.[4]

Multiracial politicians are aware of these doubts and respond strategically – participating in race-based caucuses, adopting communication styles that signal in-group membership, and making identity choices that shape their policy behavior (Brown 2014; Lemi 2017, 2026). Yet strategic signaling presupposes the underlying capacity to identify what constituents want. The question remains: do Multiracial politicians possess the contextual knowledge necessary to correctly infer Black constituency preferences?

4. For race as a heuristic, see McConnaughy et al. (2010) and Dawson (1994).

Contextual Knowledge as the Mechanism

Contextual knowledge refers to an understanding of Black community norms, preferences, and political priorities acquired through sustained exposure to majority-Black social environments. Race inextricably affects the lived experiences of Black Americans (Dawson 1994; Nunnally 2012). Through racial socialization, or the "process by which African Americans learn about and identify with the influence of race on their social status, culture, and group history in the United States," contextual knowledge is transmitted via Black social networks and Black institutions (Dawson 1994; Harris-Lacewell 2010; Nunnally 2012). Through this process, Black Americans develop collective strategies for navigating racial subjugation (Harris-Lacewell 2010). These strategies help develop what Harris-Lacewell (2010) calls an "ideology" that impacts everyday Black political life. This ideology, maintained and reinforced by social constraints (White and Laird 2020), shapes Black political behavior broadly. Building on this literature, I argue that contextual knowledge enables racial competence by equipping leaders with the ability to anticipate how policies will affect Black communities.

Multiracial Americans, however, often lack the forms of racial socialization required to develop contextual knowledge and, by extension, racial competency. Importantly, the decision to identify as Multiracial, Biracial, or another mixed category is not exogenous to these processes, but instead reflects differential exposure and engagement with Black social networks and institutions (Rockquemore 1999; Rockquemore and Brunsma 2002; Root 1990). Because Black socialization generates both contextual knowledge and normative pressure to engage in group-based politics (Davis 1991; Harris-Lacewell 2010; White and Laird 2020), the choice to distinguish oneself from the Black group is not merely descriptive; it carries downstream consequences for political judgment and representation.

Consistent with this account, Multiracial Americans socialized in predominantly White environments are more likely to identify as such, and pre-adult racial context strongly predicts racial composition in adulthood (Rockquemore 1999; Rockquemore and Brunsma 2002). For Multiracials who choose a Multiracial identity, this continuity reinforces limited exposure to Black social contexts across the life course, constraining the development and updating of contextual knowledge that shapes political decision-making.

Because racial competence requires contextual knowledge, and contextual knowledge is acquired through socialization in Black environments, Multiracials with less Black socialization will be less able to infer Black constituency preferences from demographic information alone. This deficit should be domain-specific: it will manifest most clearly when policy decisions require particularized knowledge of Black community preferences rather than positions that are nationally legible.

I distinguish between universal and particularized policy domains following Johnson (2026). Universal domains involve issues where preferences are broadly predictable from partisanship or national trends. Voters' positions on Medicare expansion or abortion rights, for example, can be largely inferred from partisan identification rather than from group-specific knowledge. Particularized domains, by contrast, require contextual knowledge of how specific communities experience an issue. In these domains, demographic information alone is insufficient; representatives must draw on lived experience or sustained engagement with the group to correctly identify preferences.

Community policing represents a particularized domain for Black constituents. Unlike Medicare or abortion, where preferences largely track partisanship, Black attitudes toward policing are shaped by community-specific experiences with law enforcement (Soss and Weaver 2017). As a race-class subjugated community, the carceral state also shapes Black experiences with government, lowering trust and political efficacy (Branton, Carey, and Martinez-Ebers 2023; Soss and Weaver 2017). Moreover, exposure to police violence, whether direct or vicarious through community networks, shapes political attitudes and mobilization in ways that are transmitted through Black social contexts (Branton and Carey 2025). Support for community policing initiatives, in particular, reflects a tension between desires for public safety and deep skepticism of police institutions, one that varies across Black communities and cannot be resolved through heuristics alone (Forman 2017; Fortner 2015).[5] Correctly inferring Black constituency preferences on this issue thus requires the kind of contextual knowledge that Multiracial politicians, if less socialized in Black environments, may lack.

If contextual knowledge underlies racial competence, and Multiracial Americans are less likely to have acquired such knowledge through socialization, then Multiracial respondents should exhibit lower accuracy when inferring Black constituency preferences under uncertainty. This deficit should emerge specifically in particularized domains, where demographic cues must be translated into policy inferences, but not in universal domains where preferences track national partisan trends. I test these expectations using an experimental design that manipulates information availability and policy domain.

Hypotheses

The preceding theoretical framework generates several testable predictions. If racial competence requires contextual knowledge acquired through socialization in Black environments, then Multiracial respondents, who are less likely to have such socialization, should exhibit deficits in correctly inferring Black constituency preferences. These deficits should be conditional on information availability and policy domain.

H1: No Multiracial Deficit Under Complete Information. When district preferences are directly observable (Informed condition), Multiracial respondents will perform at least as well as Black Monoracial respondents. In the absence of inferential demands, contextual knowledge is unnecessary.

H2: Multiracial Learning Deficit Under Uncertainty. When district preferences must

5. See also Jefferson (2023) for a conversation on the role of respectability politics and support for racialized punitive social policies.

be inferred from demographic information alone (Uninformed condition), Multiracial respondents will exhibit a learning disadvantage relative to Black Monoracial respondents. Specifically, the alignment gap between Multiracial and Black Monoracial respondents will widen across rounds.

H2b: Dynamic Expression of the Learning Deficit. The Multiracial learning disadvantage under uncertainty will manifest dynamically over time.

H3: Domain Specificity. The Multiracial learning deficit described in H2 will emerge in community policing, a particularized policy domain that requires contextual knowledge, but not in Medicare or abortion rights, which are universal domains.

H4: Contextual Knowledge as a Moderator. Among respondents in the Uninformed condition, greater exposure to Black social contexts will improve alignment for Multiracial respondents, attenuating baseline deficits in racial competence.

Research Design

Experimental Design

To examine whether Multiracial respondents can correctly infer Black constituency preferences from demographic information, I use an experimental design combining between-subjects random assignment with a within-subjects repeated-measures structure that places respondents in the role of a politician seeking re-election. Black-White Multiracials ($N = 153$) and Black Monoracials ($N = 180$) were recruited for this pilot study via Prolific to participate in the experiment.[6] Mixed-race status was determined through a question that asked respondents whether they self-identified as Multiracial or otherwise. A series of pre-treatment questions on demographics, political orientation, and racial identity was asked. After that, respondents were told they would be playing a repeated game as an incumbent politician seeking re-election. Figure 1 displays the overview of the game.

Respondents were told that the public will vote between the *Incumbent Profile* and the *Challenger Profile*, and were then given the algorithm that determines the election outcome. The voter's decision is non-strategic and simulated based on alignment between the district demographics and the position on funding for local community policing initiatives.[7] If the district is majority-Black (majority-White), the aligned response is to select "support" ("oppose"). This mapping reflects documented patterns in Black public opinion on community policing initiatives (see Theory section). The game repeats for a total of ten rounds, with

6. While the sample sizes are small, the repeated measure design increases the total observations to approximately $N = 3000$.

7. As noted in Figure 1, the outcome is determined by d where $d = 0$ if their stance matches the district's stance; otherwise, $d = 1$. What is withheld from the respondent is that the district's demographics determine the correct response.

Figure 1: Overview of Experimental Task for Respondents

Welcome!

You are an **incumbent running for re-election**. Across several short rounds, you will make **strategic campaign decisions**.

What You'll Do

- View a **Challenger Profile** with information about the opponent and your district.
- Choose your stance on **community policing, Medicare, and Roe v. Wade** ("Oppose" or "Support").
- See whether you won re-election for that round.

What the Public Sees
Your demographic information and your chosen stance appear in your **Incumbent Profile** and are shown to voters alongside the challenger's profile.

How Outcomes Are Determined
Each round, **your stance is compared to the district's majority view** on the same two-point scale ("Support" or "Oppose"). We define:

$$d = 0 \text{ if your stance matches the district's stance; otherwise } d = 1.$$

$$\text{Win} = 1 \text{ if } d = 0; \text{ otherwise Win} = 0.$$

Payments:

- Base payment: **$5.00** for completing the study.
- Per-round bonus: **$0.35 × Win** (i.e., $0.35 if you win that round; $0.00 otherwise).
- Total bonus = $\sum$ round bonuses; it is added automatically at the end.

Intuition: If your public stance matches what most voters in your district prefer for that round, you win re-election for that round.

Get Ready
Your goal is simple: **stay in office**. Choose strategically—your public stance and the district's response determine re-election.

an incentive of $.35 paid out each time the respondent wins re-election for that round.[8] The purpose of the repeated game is to simulate both changes in the electorate across rounds as well as to determine whether respondents update strategically throughout the game.

After viewing the game overview, respondents will see their incumbent profile, the challenger profile, and the district context. For the incumbent profile, the respondents' age, occupation, party, and education will be displayed. The challenger profile is identical except for the addition of the challenger's name. Finally, the district context displays the district's demographics and the median voter's positions across the three policies. Each attribute for the challenger is randomized, as well as the district context variables. Table 1 highlights all of the attributes as well as the levels for each.

While all attributes are randomized, the main manipulations are the challenger's name, district demographics, and the position on funding for local community policing initiatives. Challenger's name provides a measure of quality, with Black (White) names corresponding to high-quality candidates in majority-Black (majority-White) districts. Names are used in place of images because previous research has shown a comparable effect of using stereotypical names (Abrajano, Elmendorf, and Quinn 2018). District demographics are manipulated to measure how the issue of the day and the correct policy response change with the pivotal voter being either Black or White.

Treatment conditions

Figure 2 shows the timeline of the experimental procedure. All respondents play an initial baseline round where the race of the challenger, the district demographics, and the median voter's position are held constant as Black name, majority-Black, and support. The intent of the baseline round is to serve as a control period prior to the between-subjects manipulation. After, respondents are randomly assigned to either the informed or uninformed condition. In the informed condition, all information about the district is available to the respondent. Importantly, the position on community policing is available. In the uninformed condition, the only policy information given to respondents are the positions on Medicare and *Roe v. Wade*, as well as whether the district is majority-Black or majority-White. The purpose of this manipulation is to determine whether Multiracials align their position with the district's correct position absent what that position is. If Multiracials possess the same contextual knowledge as Monoracials, district demographics alone should be sufficient to infer the correct position, and no performance gap should emerge. My theory predicts otherwise. I also utilize the conjoint design to vary the attributes available in both the informed and uninformed conditions, creating a within-subjects design within each between-subjects treatment. As a result, the mixed design yields higher statistical power.[9]

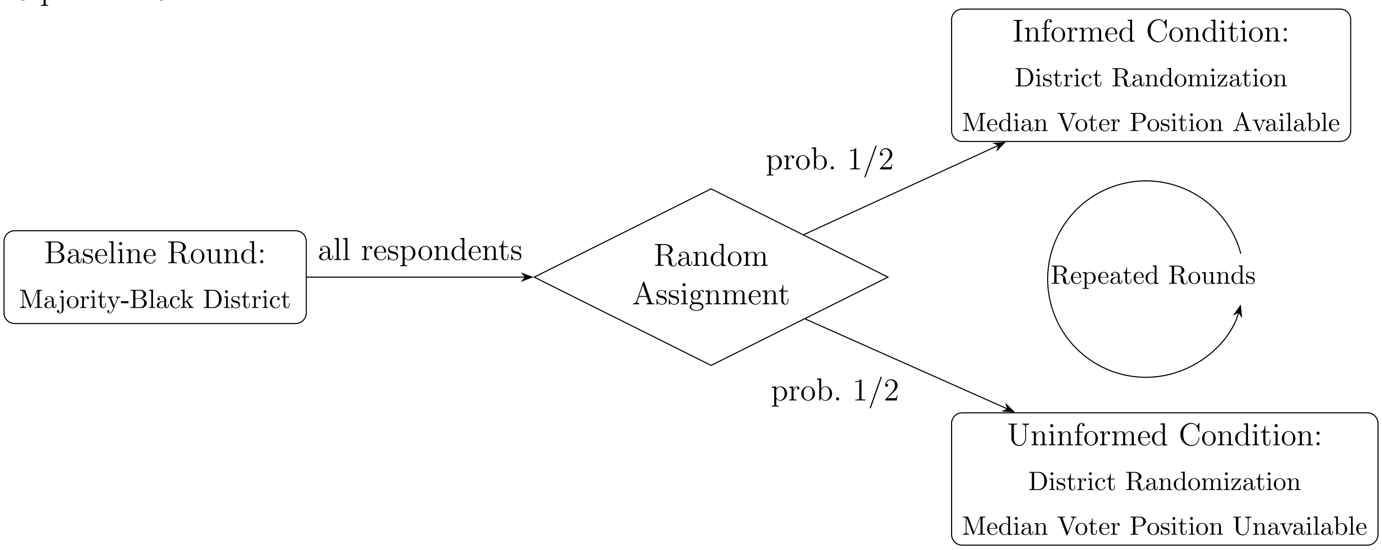
8. Each participant was paid $5.00 for partaking in the survey and awarded a bonus of $.35 for each round they won. Therefore, the total potential earnings were $8.50.

9. While there are concerns that repeated measure designs can bias treatment effects, Clifford, Sheagley, and Piston (2021) show that within-subjects designs produce similar findings as between-subjects randomization while improving statistical precision.

Table 1: Attributes and Levels in the Election Conjoint Experiment

Attribute	**Levels**
Challenger's name	Randomly drawn from a list of 20 first-and-last names: **Black names:** {Darnell Johnson; Tyrone Carter; Jamal Robinson; Marcus Allen; DeAndre Miller; Malik Thomas; Terrence Walker; Andre Coleman; Rashad Parker; Corey Jackson} **White names:** {Ethan Smith; Liam Anderson; Noah Wilson; Mason Clark; Lucas Walker; Owen Bennett; Caleb Rogers; Logan Brooks; Nathan Perry; Ryan Mitchell}.
Age	Randomly drawn $\mathbb{N}$.
Occupation	Community organizer; City council member.
Party	Democrat; Independent.
Education	Grades 1–8; Some high school, but did not graduate; High school graduate or GED; Some college; Associates, 2-year degree; Bachelors, 4-year degree; Post-graduate degree.
District demographics	65% Black, 30% White; 70% White, 20% Black.
Position on funding for local community policing initiatives	Support; Oppose.
Position on expanding Medicare to cover all Americans	Support; Oppose.
Position on the Supreme Court's decision to overturn *Roe v. Wade*	Support; Oppose.

Figure 2: Timeline of Experimental Procedure: Baseline Round, Random Assignment, and Repeated Rounds



Balance Test and Exclusion Criteria

Balance tests were conducted on the sample to ensure randomization across demographics was successful. Appendix section A.2 provides the findings. Most key demographics were slightly balanced, except for age; as a result, I opted to show models with and without demographic controls. Moreover, partisanship was borderline. Therefore, I also include party identification as a control. All analyses excluded respondents who failed attention and manipulation checks (see Appendix A.4.3).

Hierarchical Model Specifications

Given the hierarchical nature of my design (respondent i repeats ten rounds t), I utilize a multilevel model with a random intercept to allow for round-varying effects across groups (Gelman and Hill 2006). One of the main outcomes of interest is the total bonus accumulated across the ten rounds. I first utilize a linear hierarchical model. The other outcome, alignment, is binary; therefore, I use a generalized logistic hierarchical model. The structure of the model specifications is discussed below.

Total Bonus (Linear Hierarchical Model). For respondent i in round t,

$$\text{TotalBonus}_{it} = \beta_0 + \mathbf{X}_{it}\boldsymbol{\beta} + \mathbf{W}_{it}\boldsymbol{\gamma} + \mathbf{Z}_i\boldsymbol{\delta} + u_i + \varepsilon_{it}, \tag{1}$$

where

$$\mathbf{X}_{it} = \begin{pmatrix} \text{Round}_t \\ Uninformed_i \\ \text{Multiracial}_i \\ District_{it} \end{pmatrix}, \qquad \mathbf{W}_{it} = \begin{pmatrix} \text{Round}_t \times Uninformed_i \\ \text{Round}_t \times \text{Multiracial}_i \\ Uninformed_i \times \text{Multiracial}_i \\ \text{Round}_t \times Uninformed_i \times \text{Multiracial}_i \end{pmatrix},$$

$$\mathbf{Z}_i = \begin{pmatrix} \text{Age}_i \\ \text{Female}_i \\ \text{Income}_i \\ \text{Education}_i \\ \text{Party ID}_i \end{pmatrix},$$

and

$$u_i \sim \mathcal{N}(0, \sigma_u^2), \qquad \varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2).$$

TotalBonus_{it} is the cumulative bonus earned by each respondent $i \in \{1, \ldots, N\}$ for matching the correct community policing issue position to the district demographics across all ten rounds. $\mathbf{X}_{it}$ is a vector of covariates: Round_t is a indicator for each round $t \in \{1, \ldots, T\}$; Uninformed_i is whether the respondent i was assigned to the informed or uninformed treatment condition; Multiracial_i is a binary variable for whether respondent i is Multiracial or Monoracial; and District_{it} is whether the district was majority-Black or majority-White. $\mathbf{W}_{it}$ is a vector of interactions. Finally, $\mathbf{Z}_i$ is a vector of pre-treatment controls for age, gender, income, education, and party identification on a 7-point Likert scale.[10] I assume that the random intercept u_i and error ϵ_{it} are distributed normally with a mean of 0 and variance σ^2.

Alignment (Logistic Hierarchical Model). Let $A_{it} \in \{0, 1\}$ denote correct alignment. The model is

$$\text{logit}[\Pr(A_{it} = 1)] = \beta_0 + \mathbf{X}_{it}\boldsymbol{\beta} + \mathbf{W}_{it}\boldsymbol{\gamma} + \mathbf{Z}_i\boldsymbol{\delta} + u_i, \tag{2}$$

with

$$A_{it} \mid p_{it} \sim \text{Bernoulli}(p_{it}), \qquad u_i \sim \mathcal{N}(0, \sigma_u^2).$$

Let A_{it} denote whether a respondent i at round t selected the correct community policing position that reflected the displayed median voter's position (baseline/informed) or the district's demographics (uninformed). All other model components are the same as the linear model.[11]

10. All continuous control variables are in $[0, 1]$.

11. Let $\boldsymbol{\delta}$ be a vector indicator for whether the model contains control variables or not. In each regression output, I display both linear and logistic hierarchical models with and without controls. For the figures, models with full controls are utilized.

Results

Main Analysis

Total Bonus

Table 2 shows the sample demographics. Multiracial respondents were younger on average than their Monoracial peers; moreover, the Multiracial sample skewed female, consistent with findings that women are more likely to identify as mixed-race than men (Davenport 2016).[12] Mixed-race respondents are on par in terms of educational achievement, but have slightly higher income levels than Monoracials. Interestingly, Multiracials are slightly less likely to identify as Democrat than Monoracials.[13]

Table 2: Sample Demographics by Racial Group
Respondent Characteristics: Black Monoracial vs. Multiracial

	Black	**Multiracial**
N	189	153
Demographics		
Age (years)	41.74 (12.39)	34.63 (9.57)
Female	54.0%	62.1%
Education (1-7 scale)	5.33 (1.20)	5.13 (1.33)
Household Income (1-12 scale)	5.84 (3.26)	6.25 (3.39)
Democrat	65.6%	57.1%
Racial Context & Identity		
Context Scale	0.66 (0.34)	0.32 (0.38)
Racial Identity Scale	0.73 (0.19)	0.68 (0.21)

Note. Continuous variables reported as Mean (SD). Binary variables reported as percentages. Education: 1 = Less than HS, 7 = Graduate degree. Income: 1 = Under $10k, 12 = Over $150k. Context Scale: proportion of racial contexts that were majority-Black (0-1).

The key mechanism, the racial context scale, provides early evidence for the drastic differences in racialized social environment between Multiracial and Monoracial respondents. While Monoracial respondents' contextual environment represents a largely Black socialization (Mean = 0.66, SD = .34), the same cannot be said for Multiracials (Mean = 0.32, SD = .38). In effect, mixed-race respondents' racial socialization is significantly less majority-Black than their Monoracial peers ($p < 0.001$, see Appendix A.2 Table A8). And while racial identity also yields a statistically significant difference ($p < 0.05$, see Appendix A.2 Table A8), I examine whether socialization, rather than psychological group attachment, explains learning differences between Multiracial and Monoracial respondents.

To reiterate, the main outcomes of interest are the total bonus earned cumulatively across ten rounds and alignment for matching the district position (informed) or the district

12. Xu et al. (2021) find that this is localized to only first-generation Multiracial women. The pattern reverses in higher generations, so that men identify more as Multiracial than women do.

13. The measure for party identification includes strength of identity and independent-leaners.

demographics (uninformed). Table 3 presents the alignment rate and the mean final bonus for each respondent, by racial identity and treatment condition.[14] Though subtle, there is early descriptive evidence that Multiracials vary in their alignment and bonus accumulation by information structure. In informed conditions, Multiracial respondents are more aligned than Monoracials (80.8% vs 77.7%) and earn a higher average bonus (2.86 vs 2.72). In the uninformed condition, this relationship switches: Multiracial respondents are less aligned than Monoracials (45.9% vs 46.4%) and earn slightly less on average (1.74 vs 1.76).

Table 3: Descriptive Statistics by Group and Condition
Alignment Rates and Cumulative Bonus Across Experimental Conditions

			Alignment		**Final Bonus**	
Racial Identity	Information Condition	N (Respondents)	Alignment Rate	95% CI	Mean Final Bonus ($)	SD
Black	Informed	97	77.7%	[73.0%, 82.3%]	2.72	0.73
Black	Uninformed	92	46.4%	[41.7%, 51.0%]	1.76	0.71
Multiracial	Informed	74	80.8%	[75.4%, 86.2%]	2.86	0.74
Multiracial	Uninformed	79	45.9%	[40.9%, 50.8%]	1.74	0.69

Note. Alignment rate = proportion of rounds where respondent's policy choice matched district median. Final bonus = cumulative earnings after 10 rounds. 95% CI computed using normal approximation with respondent-level standard errors. Baseline round dropped.

To assess whether Multiracial respondents perform differently from their Monoracial peers across rounds, conditional on information, Table A1 in Appendix A.1.1 presents linear hierarchical models predicting cumulative bonus earnings.[15] All models include respondent-level random intercepts to account for repeated observations.

Across specifications, learning over time is evident. First, the Round variable is positive and statistically significant ($\beta = 0.275,\ p < 0.01$), indicating that respondents, on average, increase their cumulative earnings as rounds progress. Being assigned to the majority-Black district condition also increases cumulative earnings modestly for all respondents ($\beta = 0.023,\ p < 0.05$), holding other factors constant. However, learning is attenuated under uncertainty. The Round $\times$ Uninformed interaction is negative and statistically significant ($\beta = -0.102,\ p < 0.01$), suggesting that learning across rounds is substantially impaired when respondents lack information.

Turning to differences by racial group, the positive Round $\times$ Multiracial interaction ($\beta = 0.015,\ p < 0.01$) indicates that, when informed, Multiracial respondents increase their cumulative bonus at a faster rate across rounds. Consistent with H1, there is no Multiracial deficit under complete information. Indeed, Multiracial respondents exhibit a steeper learning trajectory when informed, suggesting that contextual knowledge is unnecessary, and potentially that Multiracials benefit from clear information structures. The Uninformed $\times$

14. Total bonus can be interpreted in dollars (e.g., an average of "2.72" translates to a group earning an average of $2.72.)

15. Model 1 displays findings without controls. Model 2 shows results with demographic controls. Model 3 depicts the analyses with demographic controls plus party identification. All model findings utilize the full specification unless otherwise mentioned.

Multiracial interaction is not statistically significant ($\beta = 0.044,\ p > 0.10$), indicating no baseline performance difference between groups at round one.

However, the triple interaction reveals a critical qualification. H2 predicts a learning disadvantage that emerges over time, not a static gap. The Round × Uninformed × Multiracial interaction is negative and statistically significant ($\beta = -0.016,\ p < 0.05$), indicating that across rounds, Multiracial respondents in the uninformed condition learn less and, as a result, accumulate significantly lower earnings over time. Thus, while Multiracial respondents exhibit steeper learning trajectories when informed, this advantage erodes under uncertainty, producing a relative performance penalty across rounds in the absence of information. This finding confirms H2.

Figure 3: Interaction Effects on Total Bonus
Coefficients from Model 3 (Full Controls). Reference Categories: Monoracial, Informed Condition.

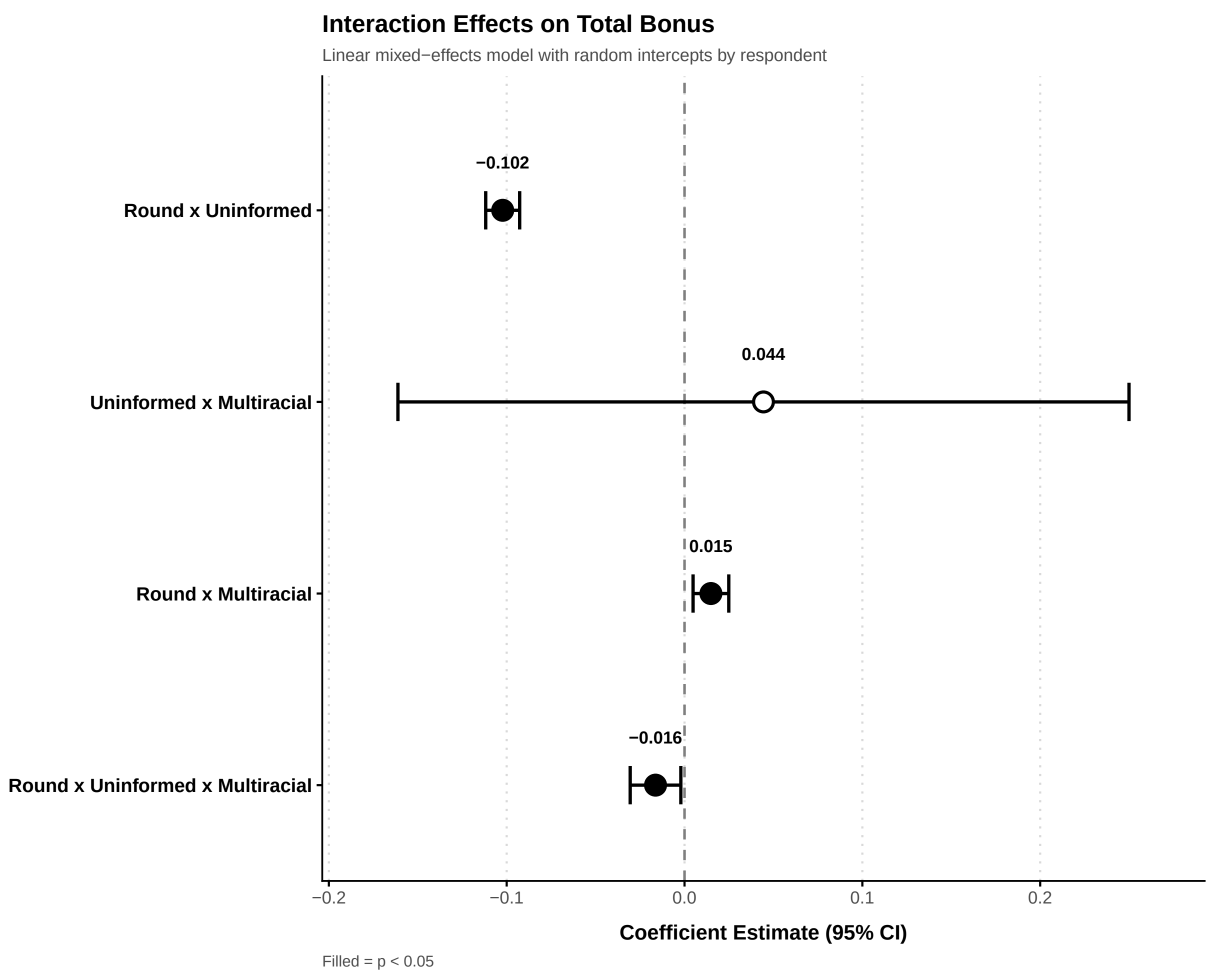


Figure 3 visualizes these estimates and highlights the relative magnitude of the interaction terms. Coefficients in bold are statistically significant ($p < 0.05$). While the Round × Multiracial coefficient signifies a steeper learning trajectory for Multiracial respondents under complete information, the corresponding effect under incomplete information is of comparable magnitude in the opposite direction. This pattern illustrates how uncertainty about the district's position on community policing disproportionately constrains Multiracial learning across rounds.

Table 4 quantifies the magnitude of the information penalty from Model 1 (Appendix A.1.1) between Black and Multiracial respondents. The information penalty is calculated as

$$\beta_1(\text{Round}) - [\beta_1 + \beta_4](\text{Round} \times \text{Uninformed}),$$

where positive values indicate slower learning under incomplete information relative to complete information, and negative values indicate faster learning when uninformed.

For Monoracial Black respondents, the information penalty is 0.103, corresponding to an approximately 37% reduction in earnings per round when respondents are uninformed. For Multiracial respondents, the information penalty is larger at 0.122, corresponding to a 42% reduction in earnings per round. Taken together, these estimates indicate that Multiracial respondents experience an information penalty roughly 5 percentage points larger than their Monoracial counterparts, translating into lower per-round earnings under uncertainty.

Table 4: Learning Rates by Group and Condition
Bonus Accumulation Per Round From Linear Hierarchical Model (Model 1)

	Learning Rate ($/round)		**Information Effect**	
Racial Identity	Informed	Uninformed	Information Penalty	% Reduction
Black	0.2756	0.1725	0.1031	37.4%
Multiracial	0.2893	0.1677	0.1216	42%

Note. Learning rates derived from Model 1 (Table 3). The informed learning rate equals β_1 (Round), and the uninformed learning rate equals $\beta_1 + \beta_4$ (Round $\times$ Uninformed). The information penalty is defined as the difference between informed and uninformed learning rates. Baseline round dropped.

Alignment

While examining total bonus provides an incentive-based measure of whether Multiracial respondents are racially competent, utilizing alignment as the outcome variable provides a more direct test. Accordingly, this section examines how the information structure impacts learning across rounds in aligning with community policing preferences. Alignment is defined as whether an incumbent correctly selects the community policing issue position that matches either the voter's ideal point (informed condition) or district demographics (uninformed condition).

Table A2 in Appendix A.1.2 presents the generalized logistic hierarchical model estimates.[16] To ease interpretation, Table 5 reports the same models expressed as odds ratios.

16. Model 1 did not converge with the baseline specification due to higher-order interactions (see Appendix

First, Round is a positive and statistically significant predictor of correctly aligning with the community policing issue position (OR = 1.13, $p < 0.01$), indicating a 13% increase in the odds of alignment across rounds for all respondents. The uninformed condition operates as expected, substantially reducing the odds of alignment by nearly 80% (OR = 0.21, $p < 0.01$). In contrast, being assigned to a majority-Black district increases the odds of alignment by approximately 75%, consistent with respondents' general ability to infer Black constituency preferences (OR = 1.75, $p < 0.01$). Unlike the continuous bonus outcome, the Round × Uninformed interaction is not statistically significant for alignment, suggesting that average learning rates do not differ by condition. However, the critical test is whether Multiracial respondents exhibit differential learning, as captured by the three-way interaction.

Table 5: Logistic Hierarchical Models: Alignment (Odds Ratios)
Dependent Variable: Alignment with District Median (1 = Yes)

	Model 1	Model 2	Model 3
Intercept	2.29***	3.12***	3.01***
	[1.47, 3.55]	[1.47, 6.60]	[1.38, 6.60]
Round	1.13***	1.13***	1.13***
	[1.05, 1.22]	[1.05, 1.22]	[1.05, 1.22]
Uninformed (U)	0.22***	0.21***	0.21***
	[0.12, 0.40]	[0.11, 0.38]	[0.11, 0.38]
Multiracial (MR)	1.03	0.90	0.81
	[0.52, 2.03]	[0.45, 1.79]	[0.40, 1.64]
Majority-Black District	1.69***	1.71***	1.75***
	[1.39, 2.06]	[1.41, 2.08]	[1.44, 2.14]
Round x Uninformed	0.95	0.95	0.95
	[0.86, 1.04]	[0.86, 1.04]	[0.86, 1.04]
Round x Multiracial	1.06	1.06	1.09
	[0.94, 1.19]	[0.94, 1.19]	[0.97, 1.22]
Uninformed x Multiracial	1.34	1.44	1.60
	[0.54, 3.30]	[0.58, 3.55]	[0.64, 4.02]
Round x Uninformed x Multiracial	0.88*	0.88*	0.85**
	[0.76, 1.02]	[0.76, 1.02]	[0.74, 0.99]
Age (scaled)		0.35**	0.34**
		[0.15, 0.81]	[0.14, 0.82]
Female		1.12	1.16
		[0.82, 1.52]	[0.84, 1.60]
Income (scaled)		1.15	1.18
		[0.68, 1.96]	[0.68, 2.05]
Education (scaled)		0.97	0.92
		[0.46, 2.07]	[0.42, 2.00]
Party ID (scaled)			1.15
			[0.74, 1.79]
Observations	3078	3051	2997

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Coefficients are odds ratios. 95% Wald confidence intervals in brackets. Random intercepts by respondent.

Turning to racial group differences, there is no statistically significant difference between Multiracial and Monoracial respondents when uninformed, mirroring results from

A.3.2). Following Lesaffre and Spiessens (2001)'s guidance for logistic mixed models with convergence issues, I re-estimated the failed models utilizing adaptive Gauss–Hermite quadrature with 3 quadrature points rather than the default Laplace approximation to improve numerical stability. Substantive conclusions are unchanged. For evidence on Laplace approximation bias with small cluster sizes, see Breslow and Lin (1995) and Rodríguez and Goldman (1995).

the linear hierarchical models. However, the triple interaction reveals an important divergence. Across rounds, Multiracial respondents in the uninformed condition experience a significant reduction in the odds of aligning with the community policing issue position (OR = 0.85, $p < 0.05$). This finding supports H2b: the interaction between round, information condition, and Multiracial status is negative, corresponding to a 15% decrease in the odds of alignment per round, indicating a learning disadvantage for Multiracial respondents under informational uncertainty. Together, these results suggest that informational uncertainty disproportionately disrupts Multiracial respondents' ability to translate learning into correct policy alignment over time.

Robustness: Medicare and *Roe v. Wade*

While the findings thus far provide evidence in support of my expectations, aligning with the two other policy issues respondents were tasked with provides a robust placebo check for the community policing issue position. The first policy issue was about whether the respondent supported or opposed Medicare for All. The second policy issue was whether the respondent supported or opposed the Supreme Court's decision in *Roe v. Wade*. Across both treatment conditions, respondents were told the district's position on each issue. An incumbent is said to have aligned with Medicare or *Roe* if they matched the district's position. If the Multiracial learning deficit also appeared for Medicare and Roe, domains where information was always available, this would suggest the deficit reflects a general learning disadvantage rather than a lack of racial competency specifically. Null findings on the placebo outcomes would support H3.

Table A3 shows the regression models for Medicare and *Roe* alignment. Due to limited variation across rounds, Medicare Model 1 and *Roe* Model 3 failed to converge with the baseline specification.[17] The limited variation supports my expectations that much of the explanation for alignment on these outcomes is driven by the clarity and nationalization of the policy positions, rather than learning or contextual updating across rounds. The only significant finding for Medicare is that the Round × Uninformed interaction increases the probability of alignment. For *Roe*, there is a slightly significant effect of learning over rounds for across all three models ($\beta = .064 - .066,\ p < 0.1$); moreover, being in a majority-Black district increases the probability of aligning with the *Roe* position across all three models ($\beta = .245 - .231,\ p < 0.05$).

Overall, these findings provide clear robustness for the pathway of racial competency. Aligning with community policing is structured through racial competency. The triple interaction – Round × Uninformed × Multiracial – was statistically significant and negative in the community policing models, highlighting Multiracial respondents' inability to update their community policing position correctly across rounds when uninformed. What is left unexplained, however, is the mechanism that contributes to racial competency. In the next

17. As with the community policing models, I re-estimated these using adaptive Gauss–Hermite quadrature (`nAGQ = 4` and `nAGQ = 3`, respectively) to address convergence issues.

section, I show that contextual knowledge through Black socialization moderates the effect of learning across rounds for Multiracial incumbents.

Mechanism: Racial Competence Through Contextual Knowledge

A central expectation is that contextual knowledge moderates the effect of learning for Multiracial respondents when aligning with community policing. Because individuals who identify as Multiracial are more likely to have been socialized in non-Black contexts, they are less likely to have developed a nuanced understanding of the lived experiences of African Americans. As a result, deficits in Black contextual knowledge constrain racial competence, inhibiting Multiracial respondents from correctly aligning with community policing issue positions.

Table 6: Context Mechanism: Odds Ratios
Dependent Variable: Alignment (Uninformed Condition Only)

	Model 1	Model 2	Model 3
Intercept	0.82	0.42	0.38
	[0.33, 2.04]	[0.12, 1.48]	[0.10, 1.45]
Round	0.92	0.91	0.91
	[0.79, 1.06]	[0.79, 1.06]	[0.79, 1.06]
Context Scale	0.34*	0.35*	0.37
	[0.10, 1.14]	[0.10, 1.20]	[0.11, 1.26]
Multiracial (MR)	0.50	0.48	0.51
	[0.17, 1.52]	[0.16, 1.49]	[0.16, 1.59]
Majority-Black District	2.05***	2.10***	2.10***
	[1.57, 2.67]	[1.61, 2.74]	[1.61, 2.76]
Round × Context	1.30***	1.31***	1.31***
	[1.07, 1.59]	[1.07, 1.59]	[1.07, 1.59]
Round × Multiracial	1.13	1.13	1.13
	[0.95, 1.35]	[0.94, 1.35]	[0.94, 1.35]
Context × Multiracial	10.70***	11.82***	10.48***
	[2.09, 54.81]	[2.28, 61.15]	[1.95, 56.35]
Round × Context × Multiracial	0.66***	0.66***	0.66***
	[0.51, 0.86]	[0.51, 0.87]	[0.50, 0.86]
Age (scaled)		0.40*	0.40
		[0.14, 1.16]	[0.14, 1.20]
Female		1.22	1.28
		[0.84, 1.76]	[0.86, 1.90]
Income (scaled)		1.39	1.50
		[0.71, 2.69]	[0.73, 3.05]
Education (scaled)		2.56*	2.37
		[0.94, 6.96]	[0.82, 6.87]
Party ID (scaled)			1.18
			[0.69, 2.05]
Observations	1188	1179	1143

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Coefficients are odds ratios. 95% Wald confidence intervals in brackets. Sample restricted to uninformed condition. Random intercepts by respondent.

Table 6 reports odds ratios from a generalized logistic hierarchical model that treats contextual knowledge as a key moderator.[18] These models are estimated on the subset of

18. See Appendix A.4.1 for the contextual knowledge scale question wording. Cronbach's $\alpha = .81$.

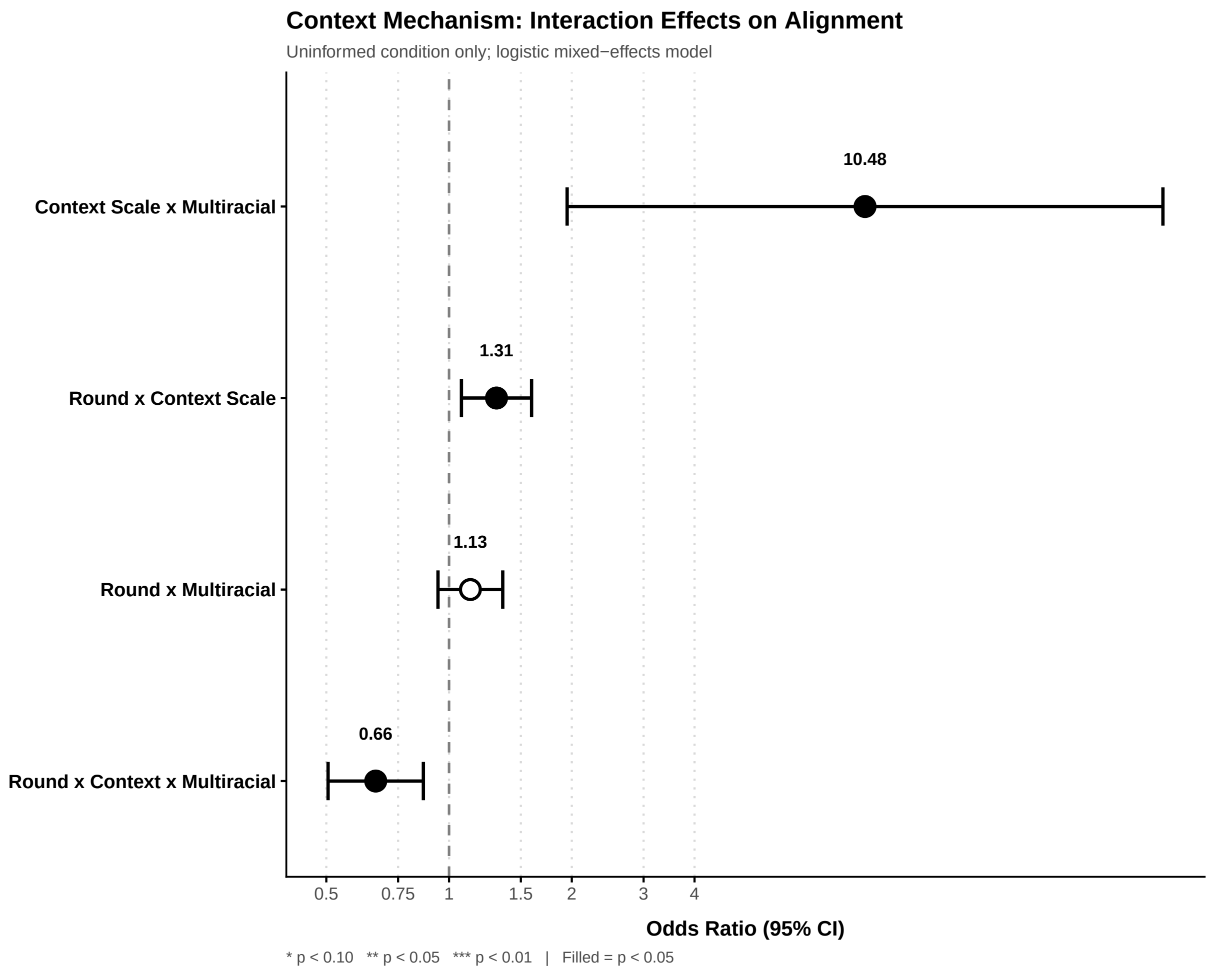
respondents in the uninformed condition, where contextual knowledge should matter most for learning and alignment (log-odds specifications are reported in Appendix A.1.4). I focus on Model 3, which includes the full set of covariates.

Across respondents, higher contextual knowledge slightly decreases the odds of correct alignment ($OR = 0.37,\ p > 0.10$), though this effect does not reach conventional levels of statistical significance. Consistent with expectations, being placed in a majority-Black district substantially increases the odds of alignment by roughly 110% ($OR = 2.10,\ p < 0.01$). Importantly, contextual knowledge moderates learning across rounds: the interaction between round and context increases the odds of correct alignment by 31% ($OR = 1.31,\ p < 0.01$), indicating that respondents with greater contextual knowledge learn the correct position more quickly over time.

H4 predicted that contextual knowledge would attenuate the Multiracial deficit. This expectation is partially supported: contextual knowledge substantially improves Multiracials' baseline alignment (Context $\times$ Multiracial : $OR = 10.48,\ p < 0.01$). However, the learning dynamics are more complex. The negative Round $\times$ Context $\times$ Multiracial interaction ($OR = 0.66,\ p < 0.01$) indicates that high-context Multiracials do not continue to improve at the same rate as their Monoracial counterparts. One interpretation is that contextual knowledge provides an initial boost for Multiracials but cannot substitute for the ongoing, reinforced socialization that Monoracial respondents experience.

Taken together, these results indicate that contextual knowledge substantially improves Multiracials' baseline alignment, but that Black respondents are better able to convert contextual knowledge into learning across repeated exposure. Contextual knowledge, therefore, compensates for Multiracials' baseline deficits in racial competence, while racial socialization allows Black respondents to learn more efficiently over time. This pattern illuminates the mechanism underlying racial competence. Contextual knowledge, as measured by exposure to Black social environments, provides Multiracials with the information needed to correctly infer constituency preferences at baseline. However, Monoracial respondents, who experience continuous reinforcement of this knowledge through ongoing socialization (Rockquemore 1999; Rockquemore and Brunsma 2002), are better positioned to update and learn over time. Racial competence thus requires not just exposure to Black contexts, but sustained embeddedness in the social networks that transmit and update political knowledge.

Figure 4: Interaction Effects on Alignment: Contextual Knowledge Mechanism (Uninformed Condition Only)



To visualize these estimates, Figure 4 presents the odds ratios from the generalized logistic model. The figure directly illustrates the proposed mechanism of racial competence through contextual knowledge: contextual knowledge substantially improves Multiracials' baseline alignment, but Black respondents are better able to translate that knowledge into learning across rounds. This pattern mirrors the interaction structure in Table 6 and highlights the role of lived racial socialization in shaping racial competence.

An Alternative Mechanism: Politicized Racial Identity

The preceding analysis demonstrates that contextual knowledge moderates the extent to which Multiracial incumbents correctly align with community policing, both when averaged across rounds and when interpreted through learning dynamics. An alternative explanation, however, is that it is not contextual knowledge per se, but rather possession of a politicized

(Black) racial identity that shapes Multiracial respondents' ability to correctly match policy positions.

Politicized racial identity is a latent psychological disposition that integrates racial salience and grievance into a broader form of group attachment (Stephens-Dougan et al. 2026). This framework builds on and updates Dawson (1994) by introducing a new measure of racial identity that more effectively predicts racialized public opinion and party identification. The core innovation of this measure is that it combines linked fate with identity importance, identity centrality, and commonly used measures of discrimination and racial resentment to capture how psychological group attachment becomes politicized and how this politicization shapes political behavior (Stephens-Dougan et al. 2026). Under this alternative account, Multiracial political behavior may be driven less by socialization through contextual knowledge and more by psychological attachment to Black group identity.

To evaluate this alternative mechanism, I partially recreate the politicized racial identity measure using six of the eight original items.[19] Table 7 reports odds ratios from generalized logistic hierarchical models estimating politicized racial identity as a moderator of alignment with community policing (log-odds specifications are provided in Appendix A.1.5).

Across all three models, politicized racial identity exhibits null effects. Neither the main effect of racial identity nor its interactions with round or Multiracial identity significantly predict correct alignment with community policing. The sole consistent predictor across specifications is district context: being placed in a majority-Black district significantly increases the odds of alignment for all respondents ($OR = 1.72,\ p < 0.01$). Importantly, no evidence suggests that politicized racial identity moderates learning or alignment for Multiracial respondents.

Taken together, these null findings are consistent with the theoretical framework advanced in this paper. Racial competence is not a function of how strongly one identifies with the Black community, but rather how much one has been socialized within it. Politicized racial identity does not substitute for the experiential knowledge acquired through sustained engagement with Black social contexts.

Discussion and Conclusion

This paper contributes to our understanding of how contextual knowledge structures Multiracial Americans' capacity for racial competence. Denzel Washington's distinction between "color" and "culture" captures a tension at the heart of descriptive representation: shared racial identity does not automatically confer the experiential knowledge necessary to represent minority constituencies substantively. Building on theories of descriptive representation and Black racial socialization, I experimentally assess whether Black-White Multira-

19. These items include Black linked fate, Black identity, two racial resentment items, and two discrimination items. Cronbach's $\alpha = .81$. For the politicized racial identity scale question wording, see A.4.2.

Table 7: Racial Identity Mechanism: Odds Ratios
Dependent Variable: Alignment (Uninformed Condition Only)

	Model 1	Model 2	Model 3
Intercept	0.43	0.36	0.33
	[0.12, 1.50]	[0.09, 1.41]	[0.08, 1.43]
Round	1.12	1.12	1.12
	[0.91, 1.37]	[0.91, 1.37]	[0.91, 1.37]
Racial Identity Scale	1.27	1.19	1.28
	[0.24, 6.63]	[0.23, 6.21]	[0.23, 7.25]
Multiracial (MR)	0.80	0.93	0.98
	[0.12, 5.24]	[0.14, 6.17]	[0.14, 6.92]
Majority-Black District	1.70***	1.73***	1.72***
	[1.36, 2.14]	[1.38, 2.17]	[1.37, 2.17]
Round × Racial Identity	0.94	0.94	0.94
	[0.72, 1.23]	[0.72, 1.23]	[0.72, 1.23]
Round × Multiracial	1.02	1.01	1.03
	[0.75, 1.38]	[0.75, 1.37]	[0.75, 1.41]
Racial Identity × Multiracial	2.12	1.71	1.62
	[0.17, 27.17]	[0.13, 22.20]	[0.11, 23.05]
Round × Racial Identity × Multiracial	0.89	0.89	0.87
	[0.59, 1.34]	[0.59, 1.34]	[0.57, 1.33]
Age (scaled)		0.42*	0.41*
		[0.17, 1.04]	[0.17, 1.03]
Female		1.03	1.07
		[0.75, 1.40]	[0.77, 1.48]
Income (scaled)		1.28	1.36
		[0.73, 2.22]	[0.76, 2.43]
Education (scaled)		1.74	1.64
		[0.76, 3.95]	[0.71, 3.80]
Party ID (scaled)			1.08
			[0.63, 1.85]
Observations	1539	1521	1485

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Coefficients are odds ratios. 95% Wald confidence intervals in brackets. Sample restricted to uninformed condition. Random intercepts by respondent.

cial respondents face learning deficits when inferring particularized constituency preferences, deficits that would constrain their capacity to deliver substantive representation. My findings demonstrate that racial competency is not an inherent trait that follows from racial identity, but a capacity that must be acquired through sustained socialization in Black environments.

For Multiracial respondents, I find that learning across rounds increases cumulative bonuses. Under complete information, Multiracial incumbents do not require contextual knowledge; they can secure reelection in each round solely on the basis of the information structure. In contrast, when district preferences must be inferred, there are significant round-to-round costs, confirming expectations that Multiracial incumbents experience a learning deficit under uncertainty. Consistent with this pattern, racial competency is also affected by the learning deficit, as uncertainty surrounding the correct community policing position constrains alignment.

As formalized in Johnson (2026), policy domain matters. When the need for contextual knowledge is present, Multiracial respondents exhibit lower racial competency. However, for universal policy domains such as Medicare and abortion, I find no significant differences between Monoracial and Multiracial incumbents in their ability to align with the correct position. These findings indicate that racial competency is not merely an artifact of the information structure but is embedded in the contextual knowledge required to infer correct positions from policy cues.

Theories of racial socialization argue that social networks and Black institutions structure Black political decision-making (Harris-Lacewell 2010; Nunnally 2012; White and Laird 2020). Because Multiracial Americans often lack lived experiences in majority-Black environments (Rockquemore 1999; Rockquemore and Brunsma 2002), I argue that contextual knowledge serves as a critical moderator of racial competency. The mechanism analysis reveals a nuanced pattern that partially supports my expectations while suggesting important qualifications. I find that greater exposure to Black social contexts improves alignment for Multiracial respondents. However, the negative triple interaction indicates that high-context Multiracials do not continue improving at the same rate as their Monoracial counterparts across repeated decisions. This pattern suggests that contextual knowledge operates differently for Multiracial and Monoracial respondents. For Monoracials, contextual knowledge may be continuously reinforced through ongoing social networks and institutional ties, enabling cumulative learning. For Multiracials, even substantial prior exposure may represent a more static knowledge stock that cannot be as readily updated in the absence of sustained embeddedness.

Several limitations warrant consideration. First, the experimental design necessarily abstracts from the complexity of real-world representation: respondents played the role of incumbents in a stylized game environment, whereas actual politicians face richer information environments, longer time horizons, and additional strategic considerations – such as challenger quality and caucus constraints – not captured here. While the formal model in Johnson (2026) addresses some of these extensions theoretically, future empirical work should examine whether the learning deficits identified in this study manifest in observed legislative behavior. Second, the sample sizes for this pilot study, while adequate for detecting the primary effects given the repeated-measures design (Clifford, Sheagley, and Piston 2021), limit statistical power for some subgroup analyses. In particular, the mechanism tests, conducted only among uninformed respondents, rely on smaller cell sizes that may obscure heterogeneous effects; replication with larger samples would strengthen confidence in these findings. Third, the contextual knowledge measure, though internally consistent, captures self-reported exposure to Black environments rather than directly measuring the political knowledge such exposure transmits. Future research should develop measures that more directly assess knowledge of Black community preferences, norms, and political priorities. Fourth, community policing serves as the focal particularized domain in this study, but racial competence may vary across policy areas: immigration, housing, or education policy may present distinct inferential demands, and future work should examine whether the Multiracial learning deficit generalizes across particularized domains or is specific to policing. Finally, this study focuses exclusively on Black–White Multiracials, whose identities are shaped by the distinct history of hypodescent and the one-drop rule in the United States (Davis 1991); whether these findings extend to other Multiracial combinations (e.g., Asian–White or Latino–White) or to other ambiguous-identity groups remains an open question.

As the American electorate grows more diverse, Multiracial politicians will increasingly occupy positions of power (Hardy-Fanta et al. 2013). This paper suggests that their capacity to deliver substantive representation to Black constituencies depends not on their identity, but on the experiential foundation that identity signals. The ambiguity that Multiracial politicians embody is not merely a challenge for voters trying to categorize them; it reflects a deeper uncertainty about whether these representatives possess the contextual knowledge necessary to navigate particularized policy domains. This finding complicates optimistic framings of Multiracial politicians as uniquely positioned to bridge racial divides (Lemi 2021; Velasquez-Manoff 2017). While their multiple perspectives may expand coalition-building possibilities, the same multiplicity may constrain their capacity for group-specific advocacy. Multiracial politicians are not policymakers with diffuse competencies; they face real constraints in domains requiring the racial competence that Monoracial representatives more reliably possess. Understanding these constraints and the institutional mechanisms that might mitigate them is essential for ensuring that descriptive representation translates into substantive gains for the communities it is meant to serve.

References

Abrajano, Marisa A, Christopher S Elmendorf, and Kevin M Quinn. 2018. "Labels vs. pictures: Treatment-mode effects in experiments about discrimination." *Political Analysis* 26 (1): 20–33.

Banducci, Susan A, Todd Donovan, and Jeffrey A Karp. 2004. "Minority representation, empowerment, and participation." *The Journal of Politics* 66 (2): 534–556.

Bobo, Lawrence, and Franklin D Gilliam Jr. 1990. "Race, sociopolitical participation, and black empowerment." *American Political Science Review* 84 (2): 377–393.

Bowen, Daniel C, and Christopher J Clark. 2014. "Revisiting descriptive representation in Congress: assessing the effect of race on the constituent–legislator relationship." *Political Research Quarterly* 67 (3): 695–707.

Branton, Regina P., and Jr. Carey Tony E. 2025. "Grave Acts: The Relationship between Contextual Exposure to Police Killings and Black Political Participation." *Political Research Quarterly* 78 (2): 540–551.

Branton, Regina P., Jr. Carey Tony E., and Valerie Martinez-Ebers. 2023. "Lethal Engagement: The Relationship between Contextual Exposure to Police Killings and External Political Efficacy." *Political Behavior* 45 (3): 1263–1283.

Breslow, Norman E, and Xihong Lin. 1995. "Bias correction in generalised linear mixed models with a single component of dispersion." *Biometrika,* 81–91.

Brown, Nadia. 2014. ""It's more than hair… that's why you should care": the politics of appearance for Black women state legislators." *Politics, Groups, and Identities* 2 (3): 295–312.

Clark, Christopher J. 2019. *Gaining voice: The causes and consequences of black representation in the American states.* Oxford University Press.

Clifford, Scott, Geoffrey Sheagley, and Spencer Piston. 2021. "Increasing precision without altering treatment effects: Repeated measures designs in survey experiments." *American Political Science Review* 115 (3): 1048–1065.

Davenport, Lauren D. 2016. "The role of gender, class, and religion in biracial Americans' racial labeling decisions." *American Sociological Review* 81 (1): 57–84.

Davis, F. James. 1991. *Who is black?: One Nation's Definition.* Penn State Press.

Dawson, Michael C. 1994. *Behind the mule: Race and class in African-American politics.* Princeton University Press.

Dovi, Suzanne. 2002. "Preferable descriptive representatives: Will just any woman, black, or Latino do?" *American Political Science Review* 96 (4): 729–743.

Ellis, William Curtis, and Walter Clark Wilson. 2013. "Minority chairs and congressional attention to minority issues: The effect of descriptive representation in positions of institutional power." *Social Science Quarterly* 94 (5): 1207–1221.

Forman, Jr., James. 2017. *Locking Up Our Own: Crime and Punishment in Black America.* Farrar, Straus / Giroux.

Fortner, Michael Javen. 2015. *Black silent majority: The Rockefeller drug laws and the politics of punishment.* Harvard University Press.

Fowler, Stephen. 2024. "Donald Trump Questions Kamala Harris's Racial Identity at NABJ Convention." NPR. Accessed January 21, 2026. https://www.npr.org/2024/07/31/nx-s1-5059091/donald-trump-nabj-interview.

Gamble, Katrina L. 2007. "Black political representation: An examination of legislative activity within US House committees." *Legislative Studies Quarterly* 32 (3): 421–447.

Gelman, Andrew, and Jennifer Hill. 2006. *Data analysis using regression and multilevel/hierarchical models.* Cambridge university press.

Gleason, Shane A, and Christopher T Stout. 2014. "Who is empowering who: Exploring the causal relationship between descriptive representation and Black empowerment." *Journal of Black Studies* 45 (7): 635–659.

Grose, Christian R. 2005. "Disentangling constituency and legislator effects in legislative representation: Black legislators or black districts?" *Social Science Quarterly* 86 (2): 427–443.

Hardy-Fanta, Carol, Pei-te Lien, Dianne Marie Pinderhughes, and Christine M Sierra. 2013. "Racial and Ethnic Identity of Elected Officials of Color: A Closer Look at a Complex Matter." In *APSA 2013 Annual Meeting Paper, American Political Science Association 2013 Annual Meeting.*

Harris-Lacewell, Melissa. 2010. *Barbershops, bibles, and BET: Everyday talk and black political thought.* Princeton University Press.

Jefferson, Hakeem. 2023. "The politics of respectability and Black Americans' punitive attitudes." *American Political Science Review* 117 (4): 1448–1464.

Johnson, Isaiah C. 2026. "Jack of All Trades, Master of None: Multiracial Politicians and Political Representation."

Lemi, Danielle Casarez. 2017. "Identity and coalitions in a multiracial era: how state legislators navigate race and ethnicity." *Politics, Groups, and Identities* 6:725–742. ISSN: 2156-5503, 2156-5511. https://dx.doi.org/10.1080/21565503.2017.1288144.

———. 2021. "Do voters prefer just any descriptive representative? The case of multiracial candidates." *Perspectives on Politics* 19 (4): 1061–1081.

———. 2026. *Doing Identity Labor: How Mixed-Race Politicians Disrupt Descriptive Representation* [in en]. 264. Oxford University Press. ISBN: 0197816819, 9780197816813. https://global.oup.com/academic/product/doing-identity-labor-9780197816813?cc=us&lang=en&.

Lesaffre, Emmanuel, and Bart Spiessens. 2001. "On the effect of the number of quadrature points in a logistic random effects model: An example." *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 50 (3): 325–335.

Leslie, Gregory, Natalie Masuoka, Sarah E. Gaither, and A. Chyei Vinluan Jessica D. Remedios. 2022. "Voter Evaluations of Biracial-Identified Political Candidates." *Social Sciences* 11 (4): 171. ISSN: 2076-0760. https://doi.org/10.3390/socsci11040171.

Mansbridge, Jane. 1999. "Should blacks represent blacks and women represent women? A contingent" yes"." *The Journal of politics* 61 (3): 628–657.

McConnaughy, Corrine M, Ismail K White, David L Leal, and Jason P Casellas. 2010. "A Latino on the ballot: Explaining coethnic voting among Latinos and the response of White Americans." *The Journal of Politics* 72 (4): 1199–1211.

Merolla, Jennifer L, Abbylin H Sellers, and Derek J Fowler. 2013. "Descriptive representation, political efficacy, and A frican A mericans in the 2008 presidential election." *Political Psychology* 34 (6): 863–875.

Minta, Michael D. 2011. *Oversight: Representing the interests of Blacks and Latinos in congress.* Princeton University Press.

Nunnally, Shayla C. 2012. *Trust in Black America: Race, discrimination, and politics.* New York University Press.

Orey, Byron D'Andra. 2000. "Black legislative politics in Mississippi." *Journal of Black Studies* 30 (6): 791–814.

Pitkin, Hanna. 1967. *The concept of representation.*

Rockquemore, Kerry A. 1999. "Between black and white exploring the "biracial" experience." *Race and society* 1 (2): 197–212.

Rockquemore, Kerry Ann, and David L Brunsma. 2002. "Socially embedded identities: Theories, typologies, and processes of racial identity among Black/White biracials." *Sociological Quarterly* 43 (3): 335–356.

Rodríguez, Germáan, and Noreen Goldman. 1995. "An assessment of estimation procedures for multilevel models with binary responses." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 158 (1): 73–89.

Root, Maria PP. 1990. "Resolving" other" status: Identity development of biracial individuals." *Women & Therapy* 9 (1-2): 185–205.

Soss, Joe, and Vesla Weaver. 2017. "Police are our government: Politics, political science, and the policing of race–class subjugated communities." *Annual Review of Political Science* 20 (1): 565–591.

Stephens-Dougan, LaFleur, Burcu Kolcak, Isaiah C. Johnson, Kaiyla Dartey, Jeron Fenton, Jasante' Howard, and Ismail K. White. 2026. "Moving Beyond Linked Fate: A New Measure of Politicized Racial Identity." Manuscript under review.

Stout, Christopher T, Katherine Tate, and Meghan Wilson. 2021. “Does Black representation matter? A review of descriptive representation for African Americans in legislative offices.” *National Review of Black Politics* 2 (1): 2–21.

Swain, Carol Miller. 1995. *Black faces, black interests: The representation of African Americans in Congress.* Harvard University Press.

Tate, Katherine. 2003. *Black faces in the mirror: African Americans and their representatives in the US Congress.* Princeton University Press.

Velasquez-Manoff, Moisés. 2017. “What Biracial People Know.” *The New York Times,* https://www.nytimes.com/2017/03/04/opinion/sunday/what-biracial-people-know.html?_r=0.

Walters, Ron. 2007. “Barack Obama and the Politics of Blackness.” *Journal of Black Studies* 38 (1): 7–29.

Wamble, Julian J. 2025. *We Choose You: How Black Voters Decide Which Candidates to Support.* Cambridge University Press.

West, Emily A. 2017. “Descriptive representation and political efficacy: Evidence from Obama and Clinton.” *The Journal of Politics* 79 (1): 351–355.

Whitby, Kenny J. 2000. *The color of representation: Congressional behavior and black interests.* University of Michigan Press.

White, Ismail K, and Chryl N Laird. 2020. “Steadfast democrats: How social forces shape Black political behavior.” In *Steadfast Democrats.* Princeton University Press.

Williams, Melissa Suzanne. 1993. *Voice, trust and memory: marginalized groups and the failings of liberal representation.* Harvard University.

Xu, Janet, Aliya Saperstein, Ann Morning, and Sarah Iverson. 2021. “Gender, generation, and multiracial identification in the United States.” *Demography* 58 (5): 1603–1630.

Young, Iris Marion. 1997. “Deferring group representation.” *Ethnicity and group rights* 39:349–376.

———. 2002. *Inclusion and democracy.* OUP Oxford.

A Appendix

Contents

A.1 Regression Output

A.1.1 Linear Hierarchical Model

Table A1: Linear Hierarchical Models: Total Bonus
Dependent Variable: Cumulative Bonus ($)

	Model 1	Model 2	Model 3
Intercept	0.199***	0.244**	0.227**
	(0.047)	(0.107)	(0.112)
Round	0.276***	0.275***	0.275***
	(0.003)	(0.003)	(0.003)
Uninformed (U)	0.006	-0.008	-0.006
	(0.068)	(0.068)	(0.069)
Multiracial (MR)	0.012	-0.026	-0.030
	(0.072)	(0.075)	(0.076)
Majority-Black District	0.022**	0.022**	0.023**
	(0.010)	(0.010)	(0.010)
Round x Uninformed	-0.103***	-0.102***	-0.102***
	(0.005)	(0.005)	(0.005)
Round x Multiracial	0.014***	0.014***	0.015***
	(0.005)	(0.005)	(0.005)
Uninformed x Multiracial	0.030	0.045	0.044
	(0.101)	(0.102)	(0.105)
Round x Uninformed x Multiracial	-0.018***	-0.018**	-0.016**
	(0.007)	(0.007)	(0.007)
Age (scaled)		-0.275**	-0.278**
		(0.135)	(0.137)
Female		0.023	0.029
		(0.050)	(0.051)
Income (scaled)		0.036	0.038
		(0.084)	(0.087)
Education (scaled)		0.050	0.048
		(0.120)	(0.122)
Party ID (scaled)			0.042
			(0.070)
Observations	3078	3051	2997

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ (Satterthwaite-adjusted p-values). Standard errors (in parentheses) are model-based from REML estimation. Random intercepts by respondent. Continuous predictors standardized to $[0, 1]$.

A.1.2 Generalized Logistic Hierarchical Model

Table A2: Logistic Hierarchical Models: Alignment
Dependent Variable: Alignment with District Median (1 = Yes)

	Model 1	Model 2	Model 3
Intercept	0.826***	1.136***	1.103***
	(0.224)	(0.383)	(0.400)
Round	0.127***	0.126***	0.125***
	(0.038)	(0.038)	(0.038)
Uninformed (U)	-1.530***	-1.576***	-1.584***
	(0.308)	(0.308)	(0.311)
Multiracial (MR)	0.027	-0.105	-0.206
	(0.347)	(0.351)	(0.357)
Majority-Black District	0.527***	0.538***	0.561***
	(0.099)	(0.100)	(0.101)
Round x Uninformed	-0.055	-0.054	-0.053
	(0.048)	(0.048)	(0.048)
Round x Multiracial	0.057	0.056	0.084
	(0.059)	(0.059)	(0.060)
Uninformed x Multiracial	0.292	0.364	0.470
	(0.460)	(0.460)	(0.470)
Round x Uninformed x Multiracial	-0.124*	-0.129*	-0.158**
	(0.074)	(0.074)	(0.075)
Age (scaled)		-1.059**	-1.068**
		(0.436)	(0.443)
Female		0.110	0.149
		(0.158)	(0.164)
Income (scaled)		0.143	0.168
		(0.271)	(0.282)
Education (scaled)		-0.030	-0.088
		(0.386)	(0.399)
Party ID (scaled)			0.139
			(0.227)
Observations	3078	3051	2997

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Coefficients are log-odds. Wald standard errors (in parentheses) computed from the Hessian matrix. Random intercepts by respondent. Optimizer: bobyqa.

A.1.3 Placebo: Medicare and Roe Generalized Logistic Hierarchical Model

Table A3: Placebo Robustness Tests: Medicare and Roe Alignment
Logistic Hierarchical Models for Placebo Policy Outcomes

	Medicare Alignment			**Roe Alignment**		
	Medicare (1)	Medicare (2)	Medicare (3)	Roe (1)	Roe (2)	Roe (3)
Intercept	1.190***	1.565***	1.445***	0.851***	1.276***	1.355***
	(0.280)	(0.528)	(0.542)	(0.230)	(0.432)	(0.448)
Round	0.025	0.026	0.025	0.064*	0.065*	0.066*
	(0.038)	(0.038)	(0.038)	(0.034)	(0.035)	(0.035)
Uninformed	-0.594	-0.631	-0.603	0.215	0.179	0.179
	(0.387)	(0.386)	(0.384)	(0.330)	(0.336)	(0.337)
Multiracial	0.366	0.222	0.316	0.466	0.343	0.364
	(0.427)	(0.433)	(0.437)	(0.354)	(0.367)	(0.372)
District Majority-Black	0.182	0.167	0.180	0.245**	0.233**	0.231**
	(0.110)	(0.111)	(0.112)	(0.105)	(0.108)	(0.109)
Round × Uninformed	0.116**	0.115**	0.116**	-0.001	-0.002	-0.002
	(0.051)	(0.051)	(0.051)	(0.048)	(0.049)	(0.049)
Round × Multiracial	-0.012	-0.012	-0.010	-0.022	-0.022	-0.012
	(0.057)	(0.057)	(0.057)	(0.052)	(0.053)	(0.054)
Uninformed × Multiracial	0.128	0.194	0.111	-0.612	-0.581	-0.623
	(0.585)	(0.585)	(0.594)	(0.495)	(0.508)	(0.517)
Round × Uninformed × MR	-0.027	-0.036	-0.041	0.058	0.052	0.039
	(0.078)	(0.078)	(0.079)	(0.072)	(0.074)	(0.076)
Age (scaled)		-1.303**	-1.319**		-1.371***	-1.378***
		(0.629)	(0.626)		(0.506)	(0.509)
Female		0.103	0.200		-0.028	-0.011
		(0.230)	(0.234)		(0.185)	(0.190)
Income (scaled)		0.083	0.043		-0.128	-0.148
		(0.395)	(0.400)		(0.317)	(0.324)
Education (scaled)		0.046	-0.097		0.241	0.150
		(0.561)	(0.567)		(0.450)	(0.459)
Party ID (scaled)			0.500			-0.056
			(0.324)			(0.263)
Observations	3078	3051	2997	3078	3051	2997

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Coefficients are log-odds. Standard errors (in parentheses) are Wald SEs from the Hessian. Random intercepts by respondent. Placebo tests examine whether treatment effects observed for community policing also appear for policies with no expected racial variation in district preferences. Null effects on Multiracial × Uninformed interactions support the racial competency mechanism.

A.1.4 Contextual Knowledge Generalized Logistic hierarchical Model

Table A4: Context Mechanism: Logistic Hierarchical Models
Dependent Variable: Alignment (Uninformed Condition Only)

	Model 1	Model 2	Model 3
Intercept	-0.204	-0.878	-0.963
	(0.469)	(0.649)	(0.681)
Round	-0.088	-0.090	-0.090
	(0.076)	(0.076)	(0.076)
Context Scale	-1.087*	-1.038*	-1.005
	(0.620)	(0.623)	(0.629)
Multiracial (MR)	-0.684	-0.726	-0.682
	(0.562)	(0.574)	(0.585)
Majority-Black District	0.717***	0.743***	0.744***
	(0.134)	(0.135)	(0.137)
Round × Context	0.264***	0.267***	0.268***
	(0.100)	(0.101)	(0.101)
Round × Multiracial	0.125	0.120	0.120
	(0.091)	(0.092)	(0.093)
Context × Multiracial	2.371***	2.470***	2.349***
	(0.833)	(0.839)	(0.858)
Round × Context × Multiracial	-0.415***	-0.410***	-0.414***
	(0.134)	(0.135)	(0.137)
Age (scaled)		-0.919*	-0.907
		(0.544)	(0.554)
Female		0.195	0.249
		(0.190)	(0.201)
Income (scaled)		0.327	0.404
		(0.339)	(0.364)
Education (scaled)		0.942*	0.862
		(0.510)	(0.543)
Party ID (scaled)			0.169
			(0.279)
Observations	1188	1179	1143

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Coefficients are log-odds. Sample restricted to uninformed condition. Context Scale measures proportion of Black racial contexts (0-1). Random intercepts by respondent.

Table A5: Context Composition Scale Reliability

Statistic	Value
Cronbach's Alpha	0.812
N Items	5.000
N Complete Cases	259.000
Mean Item-Total r	0.603
Min Item-Total r	0.384
Max Item-Total r	0.768

A.1.5 Politicized Racial Identity Generalized Logistic hierarchical Model

Table A6: Racial Identity Mechanism: Logistic Hierarchical Models
Dependent Variable: Alignment (Uninformed Condition Only)

	Model 1	Model 2	Model 3
Intercept	-0.849	-1.033	-1.113
	(0.638)	(0.701)	(0.752)
Round	0.111	0.111	0.111
	(0.103)	(0.103)	(0.103)
Racial Identity Scale	0.242	0.175	0.249
	(0.841)	(0.843)	(0.883)
Multiracial (MR)	-0.228	-0.077	-0.023
	(0.962)	(0.968)	(0.998)
Majority-Black District	0.533***	0.549***	0.545***
	(0.116)	(0.116)	(0.118)
Round × Racial Identity	-0.062	-0.061	-0.061
	(0.135)	(0.136)	(0.136)
Round × Multiracial	0.017	0.012	0.028
	(0.155)	(0.156)	(0.161)
Racial Identity × Multiracial	0.753	0.538	0.481
	(1.300)	(1.307)	(1.355)
Round × Racial Identity × Multiracial	-0.116	-0.116	-0.141
	(0.209)	(0.210)	(0.218)
Age (scaled)		-0.868*	-0.883*
		(0.464)	(0.467)
Female		0.026	0.066
		(0.160)	(0.168)
Income (scaled)		0.245	0.310
		(0.283)	(0.295)
Education (scaled)		0.552	0.492
		(0.420)	(0.429)
Party ID (scaled)			0.079
			(0.273)
Observations	1539	1521	1485

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Coefficients are log-odds. Sample restricted to uninformed condition. Racial identity scale measures affective group attachment (0-1). Random intercepts by respondent.

Table A7: Identity Composition Scale Reliability

Statistic	Value
Cronbach's Alpha	0.813
N Items	6.000
N Complete Cases	342.000
Mean Item-Total r	0.577
Min Item-Total r	0.497
Max Item-Total r	0.650

A.2 Balance Test

Table A8: Sample Demographics with Balance Tests
Two-sample t-tests Comparing Black Monoracial vs. Multiracial Respondents

	BlackMean (SD)	**Multiracial**Mean (SD)	**Diff**	**t**	**p**	
N	189	153				
Age (years)	41.74 (12.39)	34.63 (9.57)	7.107	5.98	$p < .001$	***
Female (proportion)	0.54 (0.50)	0.62 (0.49)	-0.081	-1.52	0.130	
Education (1-7)	5.33 (1.20)	5.13 (1.33)	0.197	1.43	0.155	
Household Income (1-12)	5.84 (3.26)	6.25 (3.39)	-0.417	-1.14	0.254	
Democrat (proportion)	0.66 (0.48)	0.57 (0.50)	0.085	1.58	0.116	
Context Scale (0-1)	0.66 (0.34)	0.32 (0.38)	0.334	7.37	$p < .001$	***
Racial Identity Scale (0-1)	0.73 (0.19)	0.68 (0.21)	0.049	2.26	$p < .05$	**

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Difference = Black Mean − Multiracial Mean. Two-tailed p-values from Welch's t-test (unequal variances).

A.3 Model Diagnostics

A.3.1 Model Fit: Linear Hierarchical Model

Table A9: Model Fit Statistics: Linear Hierarchical Models
Dependent Variable: Total Bonus ($)

Statistic	Model.1	Model.2	Model.3
Observations	3078.000	3051.000	2997.000
Respondents	342.000	342.000	342.000
AIC	1470.100	1478.900	1487.600
BIC	1536.500	1569.200	1583.700
Log-Likelihood	-724.100	-724.400	-727.800
Residual SD	0.253	0.253	0.254
Random Intercept SD	0.426	0.426	0.429
ICC	0.740	0.739	0.740

ICC = Intraclass Correlation Coefficient

A.3.2 Model Fit: Generalized Logistical Hierarchical Model

Table A10: Model Fit Statistics: Logistic Hierarchical Models
Dependent Variable: Align (1 = Yes)

Statistic	Model.1	Model.2	Model.3
Observations	3078.000	3051.000	2997.000
Respondents	342.000	342.000	342.000
AIC	3447.200	3425.900	3350.200
BIC	3507.500	3510.200	3440.300
Log-Likelihood	-1713.600	-1698.900	-1660.100
Random Intercept SD	1.112	1.083	1.104
ICC (latent)	0.273	0.263	0.270

$$\text{ICC}_{\text{latent}} = \frac{\text{Var(Intercept)}}{\text{Var(Intercept)} + \pi^2/3}$$

using the latent-variable approach for binary outcomes.

Table A11: Convergence Diagnostics

Model	Converged	Conv_Code	Gradient_Max	Singularity
lmer Model 1	TRUE	0	0.000009	FALSE
lmer Model 2	TRUE	0	0.000002	FALSE
lmer Model 3	TRUE	0	0.000007	FALSE
glmer Model 1	TRUE	0	0.000951	FALSE
glmer Model 2	TRUE	0	0.000760	FALSE
glmer Model 3	TRUE	0	0.001328	FALSE
glmer Medicare Model 1	TRUE	0	0.000209	FALSE
glmer Medicare Model 2	TRUE	0	0.000691	FALSE
glmer Medicare Model 3	TRUE	0	0.000138	FALSE
glmer Roe Model 1	TRUE	0	0.000572	FALSE
glmer Roe Model 2	TRUE	0	0.000241	FALSE
glmer Roe Model 3	TRUE	0	0.000686	FALSE
glmer Context Model 1	TRUE	0	0.000141	FALSE
glmer Context Model 2	TRUE	0	0.000253	FALSE
glmer Context Model 3	TRUE	0	0.000177	FALSE
glmer Identity Model 1	TRUE	0	0.000359	FALSE
glmer Identity Model 1	TRUE	0	0.000157	FALSE
glmer Identity Model 1	TRUE	0	0.000656	FALSE

Note. Conv_Code = 0 indicates successful convergence. Singularity indicates whether the estimated random-effects variance is near zero. Models are estimated using Laplace approximation unless otherwise noted. `glmer Model 1`, `glmer Medicare Model 1`, and `glmer Roe Model 3` were estimated using adaptive Gauss–Hermite quadrature (`nAGQ` > 1) to obtain a more accurate likelihood approximation.

A.4 Scale Construction and Survey Items

This subsection provides the full question wording for the scales used in the mechanism analyses, along with details on attention and manipulation checks.

A.4.1 Contextual Knowledge Scale

The contextual knowledge scale measures respondents' exposure to majority-Black social environments across the life course. The scale is constructed from five items, each recoded as binary indicators (1 = Mostly Black; 0 = Mostly White). Respondents selecting other racial compositions (Mostly Hispanic, Mostly Asian, Mostly Native American, or Racially balanced) are coded as missing for that item.[20] The final scale is the mean of non-missing items, requiring at least two valid responses for inclusion. Higher values indicate greater exposure to Black social contexts.

20. The religious services item is slightly different. See Table A.4.1.

Table A12: Contextual Knowledge Scale: Survey Items and Response Options

Item	Question Wording	Response Options
Neighborhood (Growing Up)	What was the racial composition of your neighborhood while growing up?	Mostly Black; Mostly White; Mostly Hispanic; Mostly Asian; Mostly Native American; Racially balanced between two or more racial/ethnic groups
College/University[a]	What is [was] the racial composition of your college, university, or trade school?	Mostly Black; Mostly White; Mostly Hispanic; Mostly Asian; Mostly Native American; Racially balanced between two or more racial/ethnic groups
Neighborhood (Current)	What is the racial composition of your present neighborhood?	Mostly Black; Mostly White; Mostly Hispanic; Mostly Asian; Mostly Native American; Racially balanced between two or more racial/ethnic groups
Religious Services (Current)[b]	Typically, when you attend religious services, what is the race or ethnicity of most of the other people attending?	All or most are Black or African American; All or most are White; All or most are Asian or Asian American; All or most are Hispanic or Latino; All or most are some other race or ethnicity; No one racial group makes up a majority
Friends	What is the racial composition of your closest friends today?	Mostly Black; Mostly White; Mostly Hispanic; Mostly Asian; Mostly Native American; Racially balanced between two or more racial/ethnic groups

Note. [a] College composition item displayed only to respondents reporting "Some college" or higher educational attainment.
[b] Religious services composition item displayed only to respondents reporting they attended religious services at least "a few times a year" or more.
Scale reliability: Cronbach's $\alpha = .81$.

Coding. For four items, responses were recoded as follows:

- 1 = “Mostly Black”
- 0 = “Mostly White”
- Missing = All other responses (Mostly Hispanic, Mostly Asian, Mostly Native American, Racially balanced)

Coding. The religious services item was coded similarly, but with different responses:

- 1 = “All or most are Black or African American’
- 0 = “All or most are White”
- Missing = All other responses (All or most are Hispanic, All or most are Asian, All or most are some other race, Racially balanced)

The contextual knowledge scale is computed as:

$$\text{Context Scale}_i = \frac{1}{n_i} \sum_{j=1}^{5} x_{ij}$$

where x_{ij} is the binary indicator for item j and n_i is the number of non-missing items for respondent i, with $n_i \geq 2$ required for scale construction.

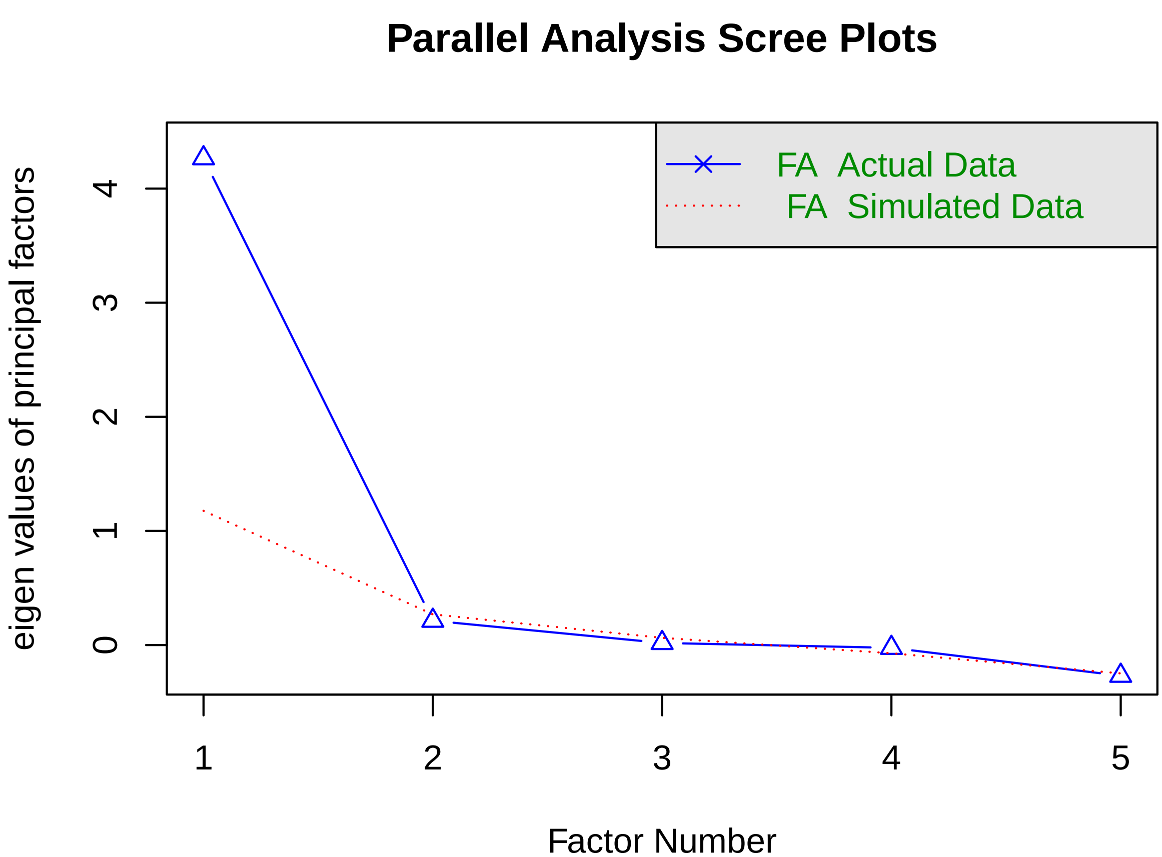
Exploratory Factor Analysis. Table A13 reports the exploratory factor analysis results for the contextual knowledge scale, including factor loadings, variance explained, and eigenvalues computed from the polychoric correlation matrix. All items load strongly onto a single latent factor, which accounts for the majority of the total variance in the scale. The eigenvalue distribution likewise indicates a clear one-factor structure, providing additional evidence of unidimensionality.

Table A13: Exploratory Factor Analysis: Contextual Knowledge Scale

	Factor 1 (ML)
Items	**Loading**
neigh_grow_black	0.967
college_comp_black	0.933
neigh_now_black	0.978
friends_black	0.998
church_black	0.670
Variance Explained	
SS loadings	4.204
Proportion variance	0.841
Eigenvalues (polychoric correlation matrix)	
1	4.393
2	0.525
3	0.081
4	0.000
5	0.000

Note. Exploratory factor analysis estimated via maximum likelihood using the polychoric correlation matrix. Loadings shown for a one-factor solution. The first factor explains 84.1% of total variance. Eigenvalues indicate a clear single-factor structure consistent with scree and parallel analysis criteria.

Figure 5: Parallel Analysis Scree Plot: Contextual Knowledge Scale



A.4.2 Politicized Racial Identity Scale

The politicized racial identity scale partially replicates the measure developed by Stephens-Dougan et al. (2026), which integrates racial salience, group attachment, perceptions of discrimination, and racial resentment into a composite indicator of politicized group consciousness. Due to survey constraints, six of the original eight items were included. The scale is the mean of non-missing items, requiring at least three valid responses for inclusion. All items are rescaled to $[0, 1]$, with higher values indicating stronger politicized racial identity.

Table A14: Politicized Racial Identity Scale: Survey Items and Response Options

Item	**Question Wording**	**Response Options**
Linked Fate	How much do you think that what happens generally to Black people in this country will affect what happens in your life?	A lot; Some; Not very much; Not at all
Identity Importance	How important is being Black or African American to your identity?	Extremely important; Very important; Moderately important; Slightly important; Not at all important
Discrimination (U.S.)	How much discrimination is there in the United States today against Black or African Americans?	A great deal; A lot; A moderate amount; A little; None at all
Discrimination (Personal)	How much discrimination have you personally felt because of your race or ethnicity?	A lot; Some; Not very much; None
Racial Resentment (Slavery)	Generations of slavery and discrimination have created conditions that make it difficult for Black people to work their way out of the lower class.	Strongly agree; Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree; Strongly disagree
Racial Resentment (Deserve)	Over the past few years, Black people have gotten less than they deserve.	Strongly agree; Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree; Strongly disagree

Note. Scale reliability: Cronbach's $\alpha = 0.81$.

Coding. Each item was rescaled to $[0, 1]$ as follows:

- **Linked Fate:** A lot = 1; Some = 0.67; Not very much = 0.33; Not at all = 0
- **Identity Importance:** Extremely important = 1; Very important = 0.75; Moderately important = 0.50; Slightly important = 0.25; Not at all important = 0
- **Discrimination (U.S.):** A great deal = 1; A lot = 0.75; A moderate amount = 0.50; A little = 0.25; None at all = 0
- **Discrimination (Personal):** A lot = 1; Some = 0.67; Not very much = 0.33; None = 0
- **Racial Resentment Items:** Strongly agree = 1; Agree = 0.83; Somewhat agree = 0.67; Neither agree nor disagree = 0.50; Somewhat disagree = 0.33; Disagree = 0.17; Strongly disagree = 0

The politicized racial identity scale is computed as:

$$\text{Identity Scale}_i = \frac{1}{n_i} \sum_{j=1}^{6} x_{ij}$$

where x_{ij} is the rescaled value for item j and n_i is the number of non-missing items for respondent i, with $n_i \geq 3$ required for scale construction.

A.4.3 Attention Check and Manipulation Check

To ensure data quality, respondents completed an attention check during the pre-treatment survey and a manipulation check after each experimental round.

Attention Check. The attention check was embedded in the pre-treatment battery and instructed respondents to select a specific response option:

Please select "strongly agree" to show you are paying attention to this question.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Respondents who failed to select "Strongly agree" were excluded from all analyses.

Manipulation Check. After each round of the experimental task, respondents were asked to confirm their understanding of their role in the game:

> *In the game previously played, did you understand that you were the Incumbent and that your profile was displayed to voters?*
>
> - Yes
> - No