# Multiracial Politicians and Political Representation: An Experimental Study*

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**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: 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.

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# 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, where preferences must be inferred, but not for Medicare or abortion, where positions are directly revealed. 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]

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

3. For a review, see Stout, Tate, and Wilson (2021).
4. For race as a heuristic, see McConnaughy et al. (2010) and Dawson (1994).

want. The question remains: do Multiracial politicians possess the contextual knowledge necessary to correctly infer Black constituency preferences?

## 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

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

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 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: 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 $\times$ 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.

Although the primary outcome of interest is alignment on community policing, the conjoint design also includes positions on Medicare and the overturn of Roe v. Wade. These issues serve two design functions. First, they operate as distractor policies that prevent respondents from fixating on community policing as the sole determinant of electoral outcomes, preserving the inferential demands of the uninformed condition. Second, because the median voter's position on Medicare and Roe v. Wade is revealed to respondents in both the informed and uninformed conditions, these issues provide placebo-matching tasks. Comparable group performance on these revealed-position items would offer indirect evidence against a general cognitive-deficit interpretation of any Multiracial disadvantage observed on community policing, where the position must be inferred rather than matched.

## 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,

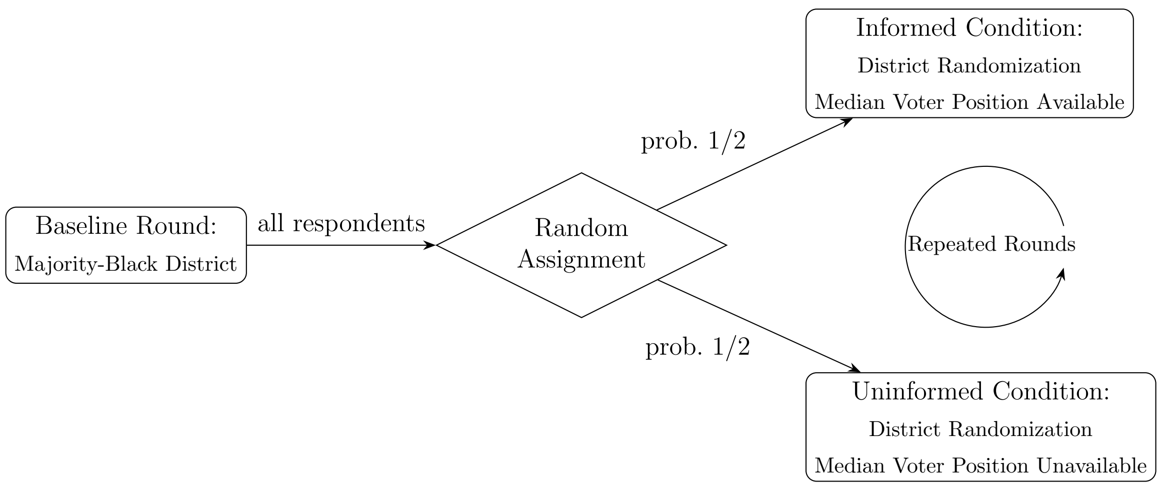
8. Each participant was paid $5.00 for partaking in the survey and awarded a bonus of $.35 for each round they won. Therefore, the total potential earnings were $8.50.

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. |

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 a conjoint design to randomize the levels of shared attributes (e.g., challenger name, district demographics, party affiliation) within each information condition, creating a within-subjects repeated-measures structure nested within the between-subjects treatment assignment. The set of displayed attributes is fixed within each treatment arm; only their values vary across rounds. As a result, the mixed design yields higher statistical power.[9]

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




## Concerns about Learning

The experimental task necessarily abstracts from the complexity of real-world constituency service. In the uninformed condition, the correct response follows a deterministic mapping from district racial composition to the aligned policy position, a design choice that allows clean identification of learning dynamics. This simplification means the task captures whether respondents recognize a substantively grounded pattern (that majority-Black districts prefer support for community policing) rather than testing the full depth of contextual knowledge a representative would deploy. However, the mapping is not arbitrary: it reflects documented patterns in Black public opinion on community policing (Forman 2017; Fortner 2015; Soss and Weaver 2017). Respondents with prior exposure to Black social contexts should recognize this association more quickly because it corresponds to real-world

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.

political dynamics they have encountered. That the learning deficit emerges specifically on the inferential task, where positions must be derived from demographic cues, rather than on the revealed-position matching tasks further supports the interpretation that contextual knowledge, rather than generic pattern detection, drives group differences.

## Balance Test and Exclusion Criteria

Balance tests were conducted on the sample to ensure randomization across demographics was successful. Appendix section A.1 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.7).

## 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 time-varying effects across groups (Gelman and Hill 2006). In the results section, I identify the causal effect utilizing a hierarchical linear model — or a linear probability model (LPM).[10] 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

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

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

10. In Appendix A.3 I provide model specifications for fixed effects with clustered standard errors at the respondent level as an alternative identification strategy. I also show logistic hierarchical models for additional robustness. Both the fixed effects and the logistic mixed effects models approximate the LPM and thus, I conclude that the findings are not sensitive to identification strategy.

and

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

$\text{TotalBonus}_{it}$ is the cumulative bonus respondent $i$ has earned through round $t$; that is, the running sum of per-round winnings ($0.35 for a correct match, $0.00 otherwise) from round 1 through round $t$. This variable therefore takes on increasing values across rounds by construction for any respondent who wins at least one round. The TotalBonus specification captures the cumulative material consequences of learning differences, while the Alignment specification below provides a direct per-round test of whether learning rates differ across groups. $\mathbf{X}_{it}$ is a vector of covariates: $\text{Round}_t$ is an indicator for each round $t \in \{1, \ldots, T\}$; $\text{Uninformed}_i$ is whether the respondent $i$ was assigned to the informed or uninformed treatment condition; $\text{Multiracial}_i$ is a binary variable for whether respondent $i$ is Multiracial or Monoracial; and $\text{District}_{it}$ 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.[11] I assume that the random intercept $u_i$ and error $\varepsilon_{it}$ are distributed normally with a mean of 0 and variance $\sigma^2$.

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

$$A_{it} = \beta_0 + \mathbf{X}_{it}\boldsymbol{\beta} + \mathbf{W}_{it}\boldsymbol{\gamma} + \mathbf{Z}_i\boldsymbol{\delta} + u_i + \varepsilon_{it}. \tag{2}$$

I assume the random intercept $u_i \sim \mathcal{N}(0, \sigma_u^2)$. Because $A_{it}$ is binary, the residual $\varepsilon_{it}$ is heteroskedastic by construction; we treat the alignment equation as specifying the conditional mean $\mathbb{E}[A_{it} \mid \mathbf{X}_{it}, u_i] = \beta_0 + \mathbf{X}_{it}\boldsymbol{\beta} + \mathbf{W}_{it}\boldsymbol{\gamma} + \mathbf{Z}_i\boldsymbol{\delta} + u_i$ and interpret coefficients as percentage-point changes in the probability of alignment. $A_{it}$ denotes whether 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 Total Bonus specification.[12]

# 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

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

12. Logistic mixed-effects robustness checks in Appendix A.3 confirm that results are not sensitive to this functional form assumption. Let $\boldsymbol{\delta}$ be a vector indicator for whether the model contains control variables or not. In each regression output, I display LPM specifications with and without controls. For the figures, models with full controls are utilized.

with findings that women are more likely to identify as mixed-race than men (Davenport 2016).[13] 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.[14]

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.1 Table A1). And while racial identity also yields a statistically significant difference ($p < 0.05$, see Appendix A.1 Table A1), 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 demographics (uninformed). Table 3 presents the alignment rate and the mean final bonus for each respondent, by racial identity and treatment condition.[15] 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).

13. 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.

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

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

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 A2 in Appendix A.2 presents linear hierarchical models predicting cumulative bonus earnings.[16] 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 $\times$ 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 $\times$ Uninformed $\times$ 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,

16. 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.

producing a relative performance penalty across rounds in the absence of information. This finding confirms H2.

## Alignment

While examining total bonus provides an incentive-based measure of whether Multiracial respondents are racially competent, total bonus is a running sum, so even a static difference in per-round win rates would produce diverging cumulative trajectories. Utilizing alignment as the outcome variable addresses this concern directly: because alignment is a binary per-round indicator, any significant interaction with Round captures a genuine change in the probability of correct alignment per round rather than arithmetic accumulation. Accordingly, this section analyzes how the information structure shapes learning across rounds in aligning with community policing preferences.

Table 4 reports linear probability mixed-effects models with respondent-level random intercepts. Because the dependent variable is binary, coefficients are interpreted as percentage-point changes in the probability of alignment. Several patterns emerge. First, Round is positive and statistically significant across all specifications ($\hat{\beta} = 0.015$, $p < 0.01$), implying that the probability of correct alignment increases by approximately 1.5 percentage points per round, consistent with learning over repeated play. Second, the uninformed condition substantially reduces performance ($\hat{\beta} \approx -0.31$, $p < 0.01$), indicating that respondents are about 31 percentage points less likely to align correctly when they must infer preferences from district demographics rather than directly observe the voter's ideal point. Third, assignment to a majority-Black district increases alignment by roughly 9 percentage points ($\hat{\beta} \approx 0.09$, $p < 0.01$), suggesting that respondents are generally able to infer the policy preferences of Black constituencies. In contrast, the Round $\times$ Uninformed interaction is small and statistically indistinguishable from zero, indicating that average learning rates do not differ systematically across information environments. Likewise, there is no evidence of baseline differences in alignment between Multiracial and monoracial respondents.

The critical test concerns heterogeneous learning among Multiracial respondents. The Round $\times$ Uninformed $\times$ Multiracial interaction is negative and marginally significant in the fully controlled specification ($\hat{\beta} = -0.021$, $p < 0.10$). This finding provides modest support for H2b: Multiracial respondents' probability of improvement per round is approximately two percentage points smaller in the uninformed condition relative to monoracial respondents. Together, these results suggest that informational uncertainty disproportionately disrupts Multiracial respondents' ability to translate learning into correct policy alignment over time.

A supplementary analysis using three-round moving averages of alignment confirms the result of the triple interaction ($\hat{\beta} = -0.016$, $p < 0.05$; see Appendix Table A13), ruling out the possibility that the dynamic pattern is driven by round-to-round noise in a binary outcome.[17]

17. A lagged feedback model further clarifies the mechanism. Previous-round success strongly predicts current-round alignment in the informed condition ($\hat{\beta} = 0.203$, $p < 0.01$), but this signal is nearly eliminated

Table 4: Linear Probability Models: Alignment

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Intercept | 0.671*** | 0.718*** | 0.711*** |
| | (0.036) | (0.062) | (0.064) |
| Round | 0.015*** | 0.015*** | 0.015*** |
| | (0.006) | (0.006) | (0.006) |
| Uninformed | -0.309*** | -0.315*** | -0.315*** |
| | (0.052) | (0.052) | (0.052) |
| Multiracial | 0.013 | -0.008 | -0.021 |
| | (0.054) | (0.056) | (0.056) |
| Majority-Black District | 0.087*** | 0.089*** | 0.092*** |
| | (0.017) | (0.017) | (0.017) |
| Round × Uninformed | -0.001 | -0.001 | -0.001 |
| | (0.008) | (0.008) | (0.008) |
| Round × Multiracial | 0.004 | 0.003 | 0.006 |
| | (0.008) | (0.008) | (0.008) |
| Uninformed × Multiracial | 0.050 | 0.063 | 0.079 |
| | (0.077) | (0.077) | (0.078) |
| Round × Uninformed × Multiracial | -0.017 | -0.018 | -0.021* |
| | (0.012) | (0.012) | (0.012) |
| N | 3078 | 3051 | 2997 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

*Note:* Entries report linear probability models predicting alignment. Standard errors are in parentheses. All specifications include random intercepts for respondents. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

under uncertainty (net effect: $0.203 - 0.421 = -0.22$). Critically, the Uninformed × Multiracial × $A_{t-1}$ interaction is null ($\hat{\beta} = -0.009$, $p > 0.1$), indicating that both groups are equally unable to use previous-round feedback under uncertainty. The Multiracial deficit therefore operates through baseline contextual knowledge rather than differential responsiveness to feedback (see Appendix Table A14).

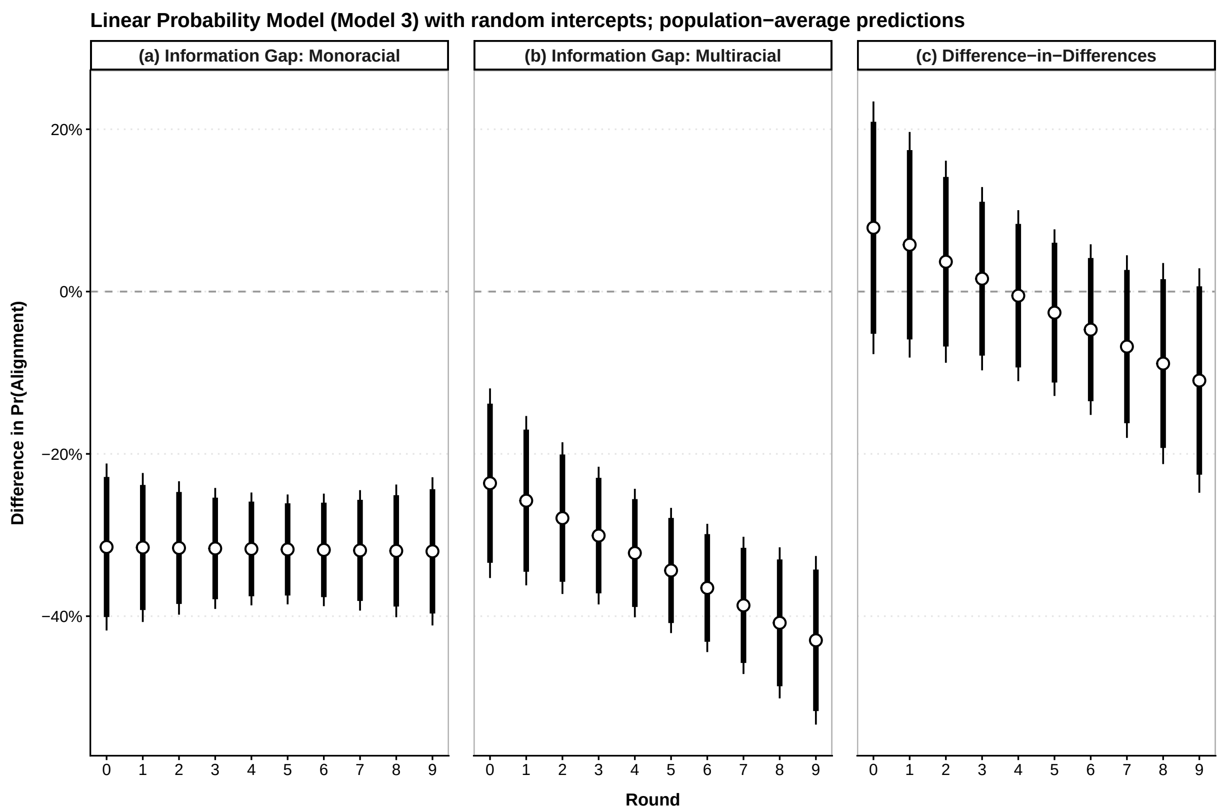



Figure 3: Information and Multiracial Identification Interaction Effects on Alignment by Round. Predicted differences from LPM with respondent random intercepts (Table 4, Model 3); covariates at sample means. Panels (a)–(b): first difference between uninformed and informed respondents within each group. Panel (c): difference-in-differences. Dashed line at zero indicates no information effect in (a)–(b) and equal gaps across groups in (c); the quantity of interest is the *trajectory* across rounds. Thick bars: 90% CIs; thin bars: 95% CIs.

Figure 3 visualizes the dynamics of the information gap underlying the three-way interaction between round, information condition, and Multiracial identification. Panels (a) and (b) plot the information effect within each group – the difference in predicted alignment probabilities between uninformed and informed respondents at each round—separately for Monoracial and Multiracial respondents.[18] For Monoracial respondents (panel a), this gap remains relatively constant across rounds, indicating little change in the informational disadvantage over time. For Multiracial respondents (panel b), the information effect becomes increasingly negative across rounds, implying that uninformed respondents fall progressively further behind their informed counterparts.

Panel (c) plots the difference-in-differences, subtracting the Monoracial information gap from the Multiracial gap at each round.[19] This quantity corresponds to the three-way in-

18. Formally, Panels (a)–(b) plots $\Pr(\text{Align} = 1 \mid U = 1, MR = k) - \Pr(\text{Align} = 1 \mid U = 0, MR = k)$ for $k \in \{0, 1\}$, where $U$ denotes uninformed status and $MR$ denotes Multiracial identity.

19. Panel (c) plots the difference-in-differences: $\big[\Pr(\text{Align} = 1 \mid U = 1, MR = 1) - \Pr(\text{Align} = 1 \mid U = 0, MR = 1)\big] - \big[\Pr(\text{Align} = 1 \mid U = 1, MR = 0) - \Pr(\text{Align} = 1 \mid U = 0, MR = 0)\big]$.

teraction between round, information, and Multiracial identification. The negative slope indicates that the information gap widens more rapidly for Multiracial respondents than for Monoracial respondents, consistent with increasing divergence in alignment behavior across repeated rounds. This pattern suggests that informational disadvantages compound more strongly for Multiracial respondents, producing increasing divergence in alignment behavior under uncertainty, supporting H2b.[20]

## 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 5 reports linear probability models with respondent-level random intercepts that treat contextual knowledge as a key moderator.[21] These models are estimated on the subset of respondents in the uninformed condition, where contextual knowledge should matter most for learning and alignment. Because the dependent variable is binary, coefficients are interpreted as percentage-point changes in the probability of alignment. I focus on Model 3, which includes the full set of covariates.[22]

Across respondents, higher contextual knowledge is associated with a decrease in the probability of correct alignment at baseline ($\hat{\beta} = -0.202,\ p > 0.10$), though this effect does not reach conventional levels of statistical significance. Consistent with expectations, being placed in a majority-Black district increases alignment by approximately 16 percentage points ($\hat{\beta} = 0.159,\ p < 0.01$). Importantly, contextual knowledge moderates learning across rounds: the interaction between Round and Context increases the probability of correct

20. As an additional check, I examine whether group differences emerge on Medicare and Roe v. Wade, where the median voter's position is revealed in both conditions. Appendix Table A3 shows null triple interactions for both issues, indicating comparable performance on these matching tasks. This pattern provides indirect evidence against a general cognitive-deficit interpretation of the Multiracial learning disadvantage on community policing.

21. See Appendix A.6.1 for the contextual knowledge scale question wording. Cronbach's $\alpha = .81$.

22. One coding decision warrants note. The contextual knowledge scale treats "Racially balanced" responses as missing rather than assigning an intermediate value, which could exclude respondents with mixed socialization histories, precisely those most relevant to the Multiracial experience. However, the exclusion rate is nearly identical across groups (24.3% for Monoracial vs. 24.2% for Multiracial respondents), indicating that the coding choice does not differentially select on group membership (Appendix Table A15). As a sensitivity check, I recode "Racially balanced" responses as 0.5 (intermediate exposure) rather than treating them as missing, recovering 83 additional respondents. The key interactions are substantively larger and remain statistically significant under this alternative coding (Appendix Table A16), confirming that the mechanism findings are not driven by the exclusion of respondents with racially integrated backgrounds.

alignment by roughly 5.5 percentage points per round ($\hat{\beta} = 0.055,\ p < 0.01$), indicating that respondents with greater contextual knowledge learn the correct position more quickly over time.

H3 predicted that contextual knowledge would attenuate the Multiracial deficit. This expectation is partially supported: contextual knowledge substantially improves Multiracial respondents' baseline alignment (Context $\times$ Multiracial: $\hat{\beta} = 0.488,\ p < 0.01$), implying that a shift from no Black community exposure to full exposure increases the probability of alignment by nearly 49 percentage points for Multiracial respondents relative to Monoracial respondents. However, the learning dynamics are more complex. The negative Round $\times$ Context $\times$ Multiracial interaction ($\hat{\beta} = -0.086,\ p < 0.01$) indicates that high-context Multiracial respondents do not continue to improve at the same rate as their Monoracial counterparts. Each additional round reduces the contextual knowledge advantage for Multiracial respondents by approximately 8.6 percentage points relative to Monoracial respondents. One interpretation is that contextual knowledge provides an initial boost for Multiracial respondents but cannot substitute for the ongoing, reinforced socialization that Monoracial respondents experience.[23]

Figure 4 visualizes these dynamics by plotting the marginal effect of contextual knowledge on alignment probability at each round, separately by racial identification.[24] For Monoracial respondents, the marginal effect of contextual knowledge begins slightly negative in early rounds but increases steadily, reaching approximately 25–30 percentage points by round 9. This upward trajectory reflects the positive Round $\times$ Context interaction: as the game progresses, contextual knowledge becomes an increasingly powerful predictor of alignment for Monoracial respondents. For Multiracial respondents, the pattern is reversed. The marginal effect of contextual knowledge starts high, roughly 25 percentage points in round 1, but declines across rounds, approaching zero by round 9. This downward slope corresponds to the negative three-way interaction: the initial advantage that contextual knowledge confers on Multiracial respondents erodes with repeated play. The density plot in the lower panel shows that Multiracial respondents tend to have lower contextual knowledge scores than Monoracial respondents, potentially amplifying disparities in alignment.[25]

Taken together, these results indicate that contextual knowledge substantially improves Multiracial respondents' baseline alignment, but that Monoracial respondents are better able

23. An alternative interpretation is that the declining marginal effect of contextual knowledge for Multiracial respondents reflects ceiling constraints rather than a genuine failure to update. This explanation is inconsistent with the data. High-context Multiracial respondents align at approximately 54% in rounds 1–3, well below any plausible ceiling, and their alignment actually declines to approximately 40% by rounds 7–9. By contrast, high-context Monoracial respondents improve from 39% to 55% over the same interval (Appendix Table A17). A quadratic specification confirms no significant nonlinear leveling off (Appendix Table A18). The declining trajectory for high-context Multiracial respondents is therefore more consistent with a degradation of initial contextual knowledge under repeated play than with mechanical compression at the upper bound.

24. Marginal effects are computed as the discrete change in predicted probability associated with a one-unit increase in the context scale, with all other covariates held at sample means.

25. Following Hainmueller, Mummolo, and Xu (2019), I test for violations of the linear interaction assumption (LIE) for the contextual knowledge moderator. Diagnostic results are presented in Appendix A.5.2.

Table 5: Context Mechanism: Linear Probability Models

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Intercept | 0.451*** | 0.308** | 0.289* |
| | (0.100) | (0.140) | (0.147) |
| Round | -0.018 | -0.018 | -0.018 |
| | (0.016) | (0.016) | (0.016) |
| Context Scale | -0.223* | -0.211 | -0.202 |
| | (0.131) | (0.131) | (0.132) |
| Multiracial | -0.140 | -0.147 | -0.137 |
| | (0.119) | (0.121) | (0.124) |
| Majority-Black District | 0.154*** | 0.159*** | 0.159*** |
| | (0.028) | (0.028) | (0.029) |
| Round × Context | 0.055*** | 0.055*** | 0.055*** |
| | (0.021) | (0.021) | (0.021) |
| Round × Multiracial | 0.025 | 0.024 | 0.024 |
| | (0.019) | (0.019) | (0.019) |
| Context × Multiracial | 0.498*** | 0.516*** | 0.488*** |
| | (0.176) | (0.177) | (0.181) |
| Round × Context × Multiracial | -0.087*** | -0.086*** | -0.086*** |
| | (0.028) | (0.028) | (0.028) |
| N | 1188 | 1179 | 1143 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

*Note:* Entries report linear probability models predicting alignment. Standard errors are in parentheses. The sample is restricted to the Uninformed condition. The context scale ranges from 0 (no Black community exposure) to 1 (full exposure). Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

to convert contextual knowledge into learning across repeated exposure. Contextual knowledge, therefore, compensates for Multiracial respondents' baseline deficits in racial competence, while racial socialization allows Monoracial 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 Multiracial respondents 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.

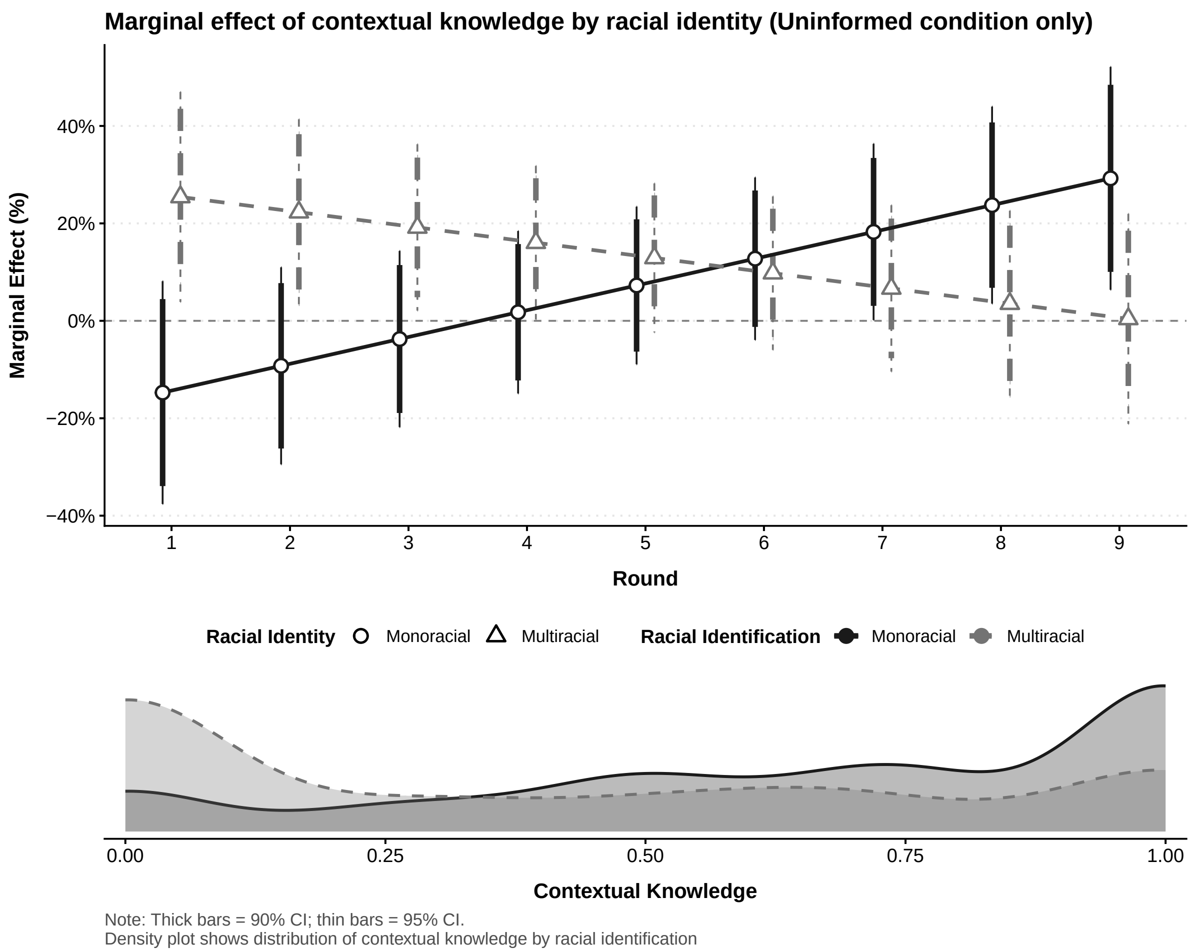



Figure 4: Marginal Effect of Contextual Knowledge on Alignment by Racial Identity and Round (Uninformed Condition). The upper panel plots the marginal effect of a one-unit increase in contextual knowledge on the probability of alignment across rounds, estimated from a linear probability model with respondent random intercepts (Table 5, Model 3). Thick bars denote 90% confidence intervals; thin bars denote 95% confidence intervals. The lower panel displays the distribution of contextual knowledge by racial identification.

## 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 measure of racial identity that more effectively predicts racialized public opinion and partisan identification. Its conceptual innovation lies in combining linked fate with identity importance, identity centrality, discrimination, and racial resentment to capture how psychological group attachment becomes politicized and shapes political behavior (Stephens-Dougan et al. 2026). Under this alternative account, Multiracial political behavior may be driven less by contextual socialization through exposure to Black environments 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.[26] Table A4 reports estimates from linear probability mixed-effects models examining politicized racial identity as a moderator of alignment with community policing.

Across all three specifications, politicized racial identity exhibits null effects. In Model 1, the main effect of the identity scale is small and statistically insignificant ($\hat{\beta} = 0.050,\ p > 0.10$). This null finding persists with demographic controls in Model 2 ($\hat{\beta} = 0.034,\ p > 0.10$) and with full controls in Model 3 ($\hat{\beta} = 0.052,\ p > 0.10$).

The interaction between identity and round is likewise null across specifications ($\hat{\beta} = -0.013,\ p > 0.10$), indicating that politicized racial identity does not shape learning dynamics over repeated rounds. Similarly, the interaction between identity and Multiracial status is statistically insignificant in all models (Model 1: $\hat{\beta} = 0.168,\ p > 0.10$; Model 2: $\hat{\beta} = 0.122,\ p > 0.10$; Model 3: $\hat{\beta} = 0.110,\ p > 0.10$). The three-way interaction between round, identity, and Multiracial status is also null (Model 3: $\hat{\beta} = -0.031,\ p > 0.10$), providing no evidence that politicized racial identity moderates learning among Multiracial respondents.

In contrast, district context remains a robust and substantively meaningful predictor across specifications. Being placed in a majority-Black district increases the probability of correct alignment by approximately twelve percentage points (Model 3: $\hat{\beta} = 0.120,\ p < 0.01$). Importantly, this effect holds regardless of respondents' level of politicized racial identity.

Taken together, these 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 in Black social contexts.

26. 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 Appendix A.6.2.

### Bundled Treatment Effects

The uninformed condition can be understood as a bundled treatment that combines information scarcity with high race-salience and feedback-based learning. This raises the question of whether the observed deficit reflects contextual knowledge specifically or some other feature of the bundle. The bundling, however, is inherent to the theoretical claim: my research question is precisely whether representatives can translate demographic composition into accurate policy inferences. Several patterns in the data further support the intended interpretation. First, if the deficit reflected differential trust in the algorithm or discomfort with using race as a decision cue, such effects should appear across all policy domains. Comparable performance on Medicare and *Roe v. Wade* matching tasks (Appendix Table A3) argues against domain-general mechanisms. Second, a comfort-based account predicts a level difference, a significant Uninformed × Multiracial interaction, but this term is null across specifications. The significant finding is a slope difference (the triple interaction with Round), indicating differential learning rates rather than differential willingness to use demographic cues. Third, the mechanism analysis shows that within the Multiracial group, respondents with greater exposure to Black social contexts perform better, consistent with contextual knowledge rather than a generic feature of the treatment bundle driving the result.

## 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 Multiracial 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), the need for contextual knowledge matters. When preferences must be inferred rather than observed, Multiracial respondents exhibit lower racial competency. Importantly, comparable group performance on Medicare and abortion, where positions were directly revealed, suggests that the Multiracial deficit is not attributable to general cognitive or attentional differences. The learning disadvantage emerges specifically where inference from contextual knowledge is required, rather than where respondents can simply match a revealed position.

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.

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# A Appendix

## Contents

## A.1 Balance Test

Table A1 reports Welch's two-sample $t$-tests comparing demographic characteristics across Black monoracial and Multiracial respondents. The covariates include age, gender, education, and income, as well as party identification in the full specification. The tests indicate a statistically significant difference in age ($p < 0.01$), while differences in the remaining covariates are small and statistically indistinguishable from zero. To ensure that any imbalance does not influence the results, all models are presented both with and without demographic controls.

Table A1: Balance Tests: Black Monoracial vs. Multiracial Respondents
Two-sample t-tests comparing demographic covariates across racial groups

| Variable | Black Mean | Multiracial Mean | Difference | t-statistic | p-value |
|---|---|---|---|---|---|
| Age | 41.741 | 34.634 | 7.107 | 5.983 | 0.000*** |
| Female | 0.540 | 0.621 | −0.081 | −1.516 | 0.130 |
| Education | 5.328 | 5.131 | 0.197 | 1.426 | 0.155 |
| Income | 5.835 | 6.252 | −0.417 | −1.143 | 0.254 |
| Democrat | 0.656 | 0.571 | 0.085 | 1.578 | 0.116 |

*Note:* Difference = Black mean − Multiracial mean. Two-tailed p-values are from Welch's two-sample $t$-test. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

## A.2 Main Regression Tables

Table A2: Linear Hierarchical Models: 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 | 0.006 | -0.008 | -0.006 |
| | (0.068) | (0.068) | (0.069) |
| Multiracial | 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 × Uninformed | -0.103*** | -0.102*** | -0.102*** |
| | (0.005) | (0.005) | (0.005) |
| Round × Multiracial | 0.014*** | 0.014*** | 0.015*** |
| | (0.005) | (0.005) | (0.005) |
| Uninformed × Multiracial | 0.030 | 0.045 | 0.044 |
| | (0.101) | (0.102) | (0.105) |
| Round × Uninformed × Multiracial | -0.018*** | -0.018** | -0.016** |
| | (0.007) | (0.007) | (0.007) |
| N | 3078 | 3051 | 2997 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

*Note:* Entries report linear mixed-effects models predicting cumulative bonus dollars at each round. Standard errors are in parentheses. All specifications include random intercepts for respondents. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A3: Placebo Tests (Linear Probability Models)

| | Medicare (1) | Medicare (2) | Medicare (3) | Abortion (1) | Abortion (2) | Abortion (3) |
|---|---|---|---|---|---|---|
| Intercept | 0.666*** | 0.725*** | 0.706*** | 0.644*** | 0.707*** | 0.721*** |
| | (0.038) | (0.073) | (0.075) | (0.035) | (0.065) | (0.067) |
| Round | 0.003 | 0.003 | 0.003 | 0.010* | 0.010* | 0.010** |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Uninformed | -0.064 | -0.067 | -0.063 | 0.054 | 0.049 | 0.049 |
| | (0.054) | (0.055) | (0.054) | (0.051) | (0.051) | (0.051) |
| Multiracial | 0.055 | 0.035 | 0.046 | 0.079 | 0.060 | 0.064 |
| | (0.057) | (0.059) | (0.059) | (0.054) | (0.055) | (0.055) |
| Majority-Black District | 0.025* | 0.023 | 0.025* | 0.036** | 0.034** | 0.033** |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.016) | (0.016) |
| Round × Uninformed | 0.018*** | 0.018** | 0.018*** | -0.000 | -0.001 | -0.001 |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Round × Multiracial | -0.002 | -0.002 | -0.002 | -0.004 | -0.004 | -0.003 |
| | (0.007) | (0.007) | (0.007) | (0.008) | (0.008) | (0.008) |
| Uninformed × Multiracial | 0.014 | 0.021 | 0.011 | -0.105 | -0.100 | -0.109 |
| | (0.080) | (0.081) | (0.082) | (0.076) | (0.076) | (0.077) |
| Round × Uninformed × Multiracial | -0.006 | -0.007 | -0.008 | 0.009 | 0.008 | 0.007 |
| | (0.010) | (0.010) | (0.010) | (0.011) | (0.011) | (0.011) |
| N | 3078 | 3051 | 2997 | 3078 | 3051 | 2997 |
| Demographic Controls | | ✓ | | | ✓ | |
| Full Controls | | | ✓ | | | ✓ |

*Note:* Entries report linear probability models predicting alignment. Standard errors are in parentheses. All specifications include random intercepts for respondents. Medicare and Abortion Rights serve as placebo (non-particularized) domains. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4: Identity Mechanism: Linear Probability Models

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Intercept | 0.316** | 0.276* | 0.257 |
| | (0.139) | (0.154) | (0.166) |
| Round | 0.024 | 0.024 | 0.024 |
| | (0.022) | (0.022) | (0.022) |
| Identity Scale | 0.050 | 0.034 | 0.052 |
| | (0.183) | (0.184) | (0.194) |
| Multiracial | -0.053 | -0.021 | -0.010 |
| | (0.210) | (0.212) | (0.219) |
| Majority-Black District | 0.118*** | 0.121*** | 0.120*** |
| | (0.025) | (0.025) | (0.026) |
| Round × Identity | -0.013 | -0.013 | -0.013 |
| | (0.029) | (0.029) | (0.029) |
| Round × Multiracial | 0.004 | 0.003 | 0.006 |
| | (0.034) | (0.034) | (0.035) |
| Identity × Multiracial | 0.168 | 0.122 | 0.110 |
| | (0.285) | (0.287) | (0.298) |
| Round × Identity × Multiracial | -0.026 | -0.025 | -0.031 |
| | (0.046) | (0.046) | (0.047) |
| N | 1539 | 1521 | 1485 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

*Note:* Entries are linear probability models of alignment with standard errors in parentheses. The sample is restricted to the Uninformed condition. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

## A.3 Alternative Model Specifications

All tables below replicate the main regression analyses using fixed-effects and logistic mixed-effects specifications. These alternative identification strategies assess whether the substantive findings are sensitive to functional form assumptions or to unobserved, time-invariant heterogeneity across respondents. Across all models, the estimates are substantively similar to those reported in the main text, and the core inferences remain unchanged. Taken together, these results indicate that the findings are robust to both model specification and identification strategy.

Table A5: Logistic Mixed Models: Alignment (Log-Odds)

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Intercept | 0.834*** | 1.136*** | 1.103*** |
| | (0.225) | (0.388) | (0.405) |
| Round | 0.127*** | 0.126*** | 0.125*** |
| | (0.038) | (0.038) | (0.038) |
| Uninformed | -1.539*** | -1.576*** | -1.583*** |
| | (0.309) | (0.310) | (0.313) |
| Multiracial | 0.029 | -0.107 | -0.209 |
| | (0.349) | (0.354) | (0.360) |
| Majority-Black District | 0.527*** | 0.539*** | 0.561*** |
| | (0.099) | (0.100) | (0.101) |
| Round × Uninformed | -0.055 | -0.055 | -0.054 |
| | (0.048) | (0.048) | (0.048) |
| Round × Multiracial | 0.057 | 0.057 | 0.085 |
| | (0.059) | (0.059) | (0.061) |
| Uninformed × Multiracial | 0.291 | 0.366 | 0.472 |
| | (0.462) | (0.464) | (0.474) |
| Round × Uninformed × Multiracial | -0.125* | -0.129* | -0.159** |
| | (0.074) | (0.074) | (0.076) |
| N | 3078 | 3051 | 2997 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

*Note:* Entries are logistic mixed-effects models predicting alignment. Coefficients are reported in log-odds with standard errors in parentheses. Models include random intercepts by respondent. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A6: Fixed Effects Models: Alignment

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Round | 0.015*** | 0.015*** | 0.015*** |
| | (0.006) | (0.006) | (0.006) |
| Majority-Black District | 0.087*** | 0.089*** | 0.092*** |
| | (0.032) | (0.032) | (0.032) |
| Round × Uninformed | -0.001 | -0.001 | -0.001 |
| | (0.008) | (0.008) | (0.008) |
| Round × Multiracial | 0.004 | 0.003 | 0.006 |
| | (0.008) | (0.008) | (0.008) |
| Round × Uninformed × Multiracial | -0.017 | -0.018 | -0.021* |
| | (0.012) | (0.012) | (0.013) |
| N | 3078 | 3051 | 2997 |
| Within $R^2$ | 0.025 | 0.025 | 0.028 |
| Adj. $R^2$ | 0.275 | 0.274 | 0.278 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |
| Respondent FE | ✓ | ✓ | ✓ |
| Clustered SEs | ✓ | ✓ | ✓ |

*Note:* Entries are fixed-effects linear probability models of policy alignment. Cluster-robust standard errors at the respondent level are reported in parentheses. Respondent fixed effects absorb all time-invariant characteristics, including Uninformed status, Multiracial status, their interaction, and demographic variables; only within-subject variation and interactions with Round are identified. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A7: Context Mechanism: Logistic Models (Log-Odds)

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Intercept | -0.205 | -0.880 | -0.965 |
| | (0.473) | (0.657) | (0.690) |
| Round | -0.088 | -0.090 | -0.090 |
| | (0.076) | (0.077) | (0.077) |
| Context Scale | -1.089* | -1.040* | -1.006 |
| | (0.625) | (0.629) | (0.635) |
| Multiracial | -0.685 | -0.728 | -0.684 |
| | (0.567) | (0.579) | (0.591) |
| Majority-Black District | 0.718*** | 0.743*** | 0.745*** |
| | (0.135) | (0.135) | (0.138) |
| Round × Context | 0.265*** | 0.268*** | 0.268*** |
| | (0.101) | (0.101) | (0.101) |
| Round × Multiracial | 0.125 | 0.121 | 0.121 |
| | (0.091) | (0.092) | (0.094) |
| Context × Multiracial | 2.374*** | 2.474*** | 2.354*** |
| | (0.841) | (0.846) | (0.866) |
| Round × Context × Multiracial | -0.416*** | -0.410*** | -0.415*** |
| | (0.135) | (0.136) | (0.138) |
| N | 1188 | 1179 | 1143 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

*Note:* Entries are logistic models predicting alignment; coefficients are reported in log-odds with standard errors in parentheses. The sample is restricted to the Uninformed condition. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A8: Context Mechanism: Fixed Effects Models

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Round | -0.018 | -0.018 | -0.018 |
| | (0.014) | (0.014) | (0.014) |
| Majority-Black District | 0.154*** | 0.159*** | 0.159*** |
| | (0.054) | (0.054) | (0.055) |
| Round × Context | 0.055*** | 0.055*** | 0.055*** |
| | (0.019) | (0.019) | (0.019) |
| Round × Multiracial | 0.025 | 0.024 | 0.024 |
| | (0.017) | (0.017) | (0.017) |
| Round × Context × Multiracial | -0.087*** | -0.086*** | -0.086*** |
| | (0.025) | (0.025) | (0.026) |
| N | 1188 | 1179 | 1143 |
| Within $R^2$ | 0.043 | 0.045 | 0.046 |
| Adj. $R^2$ | 0.146 | 0.148 | 0.152 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |
| Respondent FE | ✓ | ✓ | ✓ |
| Clustered SEs | ✓ | ✓ | ✓ |

*Note:* Entries are respondent fixed-effects linear probability models of alignment. Cluster-robust standard errors at the respondent level are reported in parentheses. The sample is restricted to the Uninformed condition. Respondent fixed effects absorb all time-invariant characteristics, including the main effects of Context Scale, Multiracial status, and their interaction; only within-subject variation and interactions with Round remain identified. Demographic controls include age, gender, income, and education (absorbed by fixed effects); full controls additionally include party identification (absorbed by fixed effects). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A9: Identity Mechanism: Logistic Models (Log-Odds)

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Intercept | -0.850 | -1.036 | -1.116 |
| | (0.644) | (0.708) | (0.760) |
| Round | 0.112 | 0.111 | 0.111 |
| | (0.103) | (0.103) | (0.103) |
| Identity Scale | 0.243 | 0.176 | 0.250 |
| | (0.848) | (0.850) | (0.892) |
| Multiracial | -0.227 | -0.075 | -0.021 |
| | (0.969) | (0.975) | (1.006) |
| Majority-Black District | 0.533*** | 0.549*** | 0.545*** |
| | (0.116) | (0.117) | (0.118) |
| Round × Identity | -0.062 | -0.061 | -0.061 |
| | (0.136) | (0.136) | (0.136) |
| Round × Multiracial | 0.017 | 0.012 | 0.028 |
| | (0.155) | (0.156) | (0.161) |
| Identity × Multiracial | 0.753 | 0.536 | 0.478 |
| | (1.310) | (1.318) | (1.366) |
| Round × Identity × Multiracial | -0.116 | -0.116 | -0.141 |
| | (0.210) | (0.211) | (0.219) |
| N | 1539 | 1521 | 1485 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

*Note:* Entries are logistic models predicting alignment; coefficients are reported in log-odds with standard errors in parentheses. The sample is restricted to the Uninformed condition. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A10: Identity Mechanism: Fixed Effects Models

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Round | 0.024 | 0.024 | 0.024 |
| | (0.018) | (0.018) | (0.018) |
| Majority-Black District | 0.118** | 0.121** | 0.120** |
| | (0.049) | (0.049) | (0.049) |
| Round × Identity | -0.013 | -0.013 | -0.013 |
| | (0.025) | (0.025) | (0.025) |
| Round × Multiracial | 0.004 | 0.003 | 0.006 |
| | (0.030) | (0.030) | (0.032) |
| Round × Identity × Multiracial | -0.026 | -0.025 | -0.031 |
| | (0.039) | (0.039) | (0.042) |
| N | 1539 | 1521 | 1485 |
| Within $R^2$ | 0.020 | 0.021 | 0.021 |
| Adj. $R^2$ | 0.118 | 0.119 | 0.120 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |
| Respondent FE | ✓ | ✓ | ✓ |
| Clustered SEs | ✓ | ✓ | ✓ |

*Note:* Entries are respondent fixed-effects linear probability models of alignment. Cluster-robust standard errors at the respondent level are reported in parentheses. The sample is restricted to the Uninformed condition. Respondent fixed effects absorb all time-invariant characteristics, including the main effects of Identity Scale, Multiracial status, and their interaction; only within-subject variation and interactions with Round remain identified. Demographic controls include age, gender, income, and education (absorbed by fixed effects); full controls additionally include party identification (absorbed by fixed effects). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A11: Domain Specificity: Placebo Tests (Logistic, Log-Odds)

| | Medicare (1) | Medicare (2) | Medicare (3) | Abortion (1) | Abortion (2) | Abortion (3) |
|---|---|---|---|---|---|---|
| Intercept | 1.190*** | 1.555*** | 1.436*** | 0.858*** | 1.277*** | 1.248*** |
| | (0.280) | (0.533) | (0.548) | (0.237) | (0.438) | (0.006) |
| Round | 0.025 | 0.026 | 0.025 | 0.064* | 0.066* | 0.067*** |
| | (0.038) | (0.038) | (0.038) | (0.035) | (0.035) | (0.005) |
| Uninformed | -0.594 | -0.624 | -0.597 | 0.213 | 0.178 | 0.187*** |
| | (0.387) | (0.389) | (0.387) | (0.339) | (0.339) | (0.006) |
| Multiracial | 0.366 | 0.221 | 0.312 | 0.467 | 0.342 | 0.350*** |
| | (0.427) | (0.437) | (0.440) | (0.365) | (0.371) | (0.006) |
| Majority-Black District | 0.182 | 0.167 | 0.180 | 0.247** | 0.234** | 0.226*** |
| | (0.110) | (0.111) | (0.112) | (0.108) | (0.108) | (0.006) |
| Round × Uninformed | 0.116** | 0.114** | 0.115** | -0.001 | -0.003 | -0.004 |
| | (0.051) | (0.051) | (0.051) | (0.049) | (0.049) | (0.005) |
| Round × Multiracial | -0.012 | -0.012 | -0.010 | -0.022 | -0.022 | -0.010* |
| | (0.057) | (0.057) | (0.058) | (0.053) | (0.053) | (0.005) |
| Uninformed × Multiracial | 0.128 | 0.190 | 0.109 | -0.614 | -0.580 | -0.570*** |
| | (0.585) | (0.590) | (0.598) | (0.510) | (0.512) | (0.006) |
| Round × Uninformed × Multiracial | -0.027 | -0.035 | -0.040 | 0.058 | 0.053 | 0.035*** |
| | (0.078) | (0.078) | (0.079) | (0.074) | (0.075) | (0.006) |
| N | 3078 | 3051 | 2997 | 3078 | 3051 | 2997 |
| Demographic Controls | | ✓ | | | ✓ | |
| Full Controls | | | ✓ | | | ✓ |

*Note:* Entries are logistic models predicting alignment. Coefficients are reported in log-odds with standard errors in parentheses. Random intercepts are included for respondents. Medicare and Abortion Rights serve as placebo (non-particularized) domains. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A12: Domain Specificity: Placebo Tests (Fixed Effects)

| | Medicare (1) | Medicare (2) | Medicare (3) | Abortion (1) | Abortion (2) | Abortion (3) |
|---|---|---|---|---|---|---|
| Round | 0.003 | 0.003 | 0.003 | 0.010** | 0.010** | 0.010** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Majority-Black District | 0.025* | 0.023* | 0.025* | 0.036** | 0.034** | 0.033** |
| | (0.013) | (0.013) | (0.013) | (0.014) | (0.014) | (0.014) |
| Round × Uninformed | 0.018** | 0.018** | 0.018** | -0.000 | -0.001 | -0.001 |
| | (0.008) | (0.008) | (0.008) | (0.007) | (0.007) | (0.007) |
| Round × Multiracial | -0.002 | -0.002 | -0.002 | -0.004 | -0.004 | -0.003 |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) |
| Round × Uninformed × Multiracial | -0.006 | -0.007 | -0.008 | 0.009 | 0.008 | 0.007 |
| | (0.011) | (0.011) | (0.011) | (0.009) | (0.009) | (0.010) |
| N | 3078 | 3051 | 2997 | 3078 | 3051 | 2997 |
| Within $R^2$ | 0.011 | 0.010 | 0.010 | 0.009 | 0.008 | 0.008 |
| Adj. $R^2$ | 0.329 | 0.329 | 0.328 | 0.233 | 0.234 | 0.235 |
| Demographic Controls | | ✓ | | | ✓ | |
| Full Controls | | | ✓ | | | ✓ |
| Respondent FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Clustered SEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Note:* Entries are respondent fixed-effects linear probability models. Cluster-robust standard errors at the respondent level are reported in parentheses. Medicare and Abortion Rights serve as placebo (non-particularized) domains. Respondent fixed effects absorb all time-invariant characteristics. Demographic controls include age, gender, income, and education (absorbed by fixed effects); full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

## A.4 Supplementary Analyses

This section presents additional analyses addressing concerns about cumulative versus per-round outcomes, context scale coding decisions, and ceiling effects.

### A.4.1 Cumulative vs. Per-Round Outcomes

Table A13: Moving Average Alignment Models (3-Round Window)

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Intercept | 0.676*** | 0.723*** | 0.717*** |
| | (0.032) | (0.061) | (0.064) |
| Round | 0.017*** | 0.018*** | 0.018*** |
| | (0.004) | (0.004) | (0.004) |
| Uninformed | -0.242*** | -0.245*** | -0.245*** |
| | (0.047) | (0.047) | (0.048) |
| Multiracial | 0.036 | 0.019 | 0.009 |
| | (0.049) | (0.050) | (0.051) |
| Majority-Black District | -0.000 | 0.000 | 0.001 |
| | (0.008) | (0.008) | (0.008) |
| Round × Uninformed | -0.009* | -0.009* | -0.009* |
| | (0.005) | (0.005) | (0.005) |
| Round × Multiracial | 0.000 | 0.000 | 0.002 |
| | (0.005) | (0.006) | (0.006) |
| Uninformed × Multiracial | 0.036 | 0.045 | 0.057 |
| | (0.069) | (0.070) | (0.071) |
| Round × Uninformed × Multiracial | -0.014* | -0.014* | -0.016** |
| | (0.008) | (0.008) | (0.008) |
| N | 2394 | 2373 | 2331 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

*Note:* Entries report linear probability models predicting alignment. Standard errors are in parentheses. The dependent variable is the 3-round trailing moving average of alignment. The sample is restricted to rounds $\geq 3$. All specifications include random intercepts by respondent. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A14: Lagged Feedback Updating Models: Linear Probability Models

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Intercept | 0.578*** | 0.600*** | 0.594*** |
| | (0.048) | (0.070) | (0.072) |
| Round | 0.006 | 0.006 | 0.005 |
| | (0.006) | (0.007) | (0.007) |
| Uninformed | -0.056 | -0.064 | -0.064 |
| | (0.066) | (0.067) | (0.067) |
| Multiracial | 0.006 | -0.012 | -0.021 |
| | (0.075) | (0.076) | (0.076) |
| Alignment $_{t-1}$ | 0.207*** | 0.203*** | 0.203*** |
| | (0.039) | (0.039) | (0.039) |
| Majority-Black District | 0.073*** | 0.074*** | 0.077*** |
| | (0.017) | (0.017) | (0.017) |
| Round × Uninformed | 0.001 | 0.001 | 0.002 |
| | (0.009) | (0.009) | (0.009) |
| Round × Multiracial | -0.003 | -0.003 | -0.001 |
| | (0.010) | (0.010) | (0.010) |
| Uninformed × Multiracial | 0.060 | 0.077 | 0.081 |
| | (0.099) | (0.100) | (0.101) |
| Uninformed × Alignment $_{t-1}$ | -0.422*** | -0.420*** | -0.421*** |
| | (0.050) | (0.050) | (0.050) |
| Multiracial × Alignment $_{t-1}$ | 0.051 | 0.053 | 0.054 |
| | (0.062) | (0.062) | (0.063) |
| Round × Uninformed × Multiracial | -0.014 | -0.015 | -0.017 |
| | (0.014) | (0.014) | (0.014) |
| Uninformed × Multiracial × Alignment $_{t-1}$ | -0.025 | -0.022 | -0.009 |
| | (0.077) | (0.078) | (0.079) |
| N | 2736 | 2712 | 2664 |
| $R^2$ (Marginal) | 0.168 | 0.168 | 0.169 |
| $R^2$ (Conditional) | 0.305 | 0.305 | 0.307 |
| AIC | 3179.3 | 3175.3 | 3114.2 |
| BIC | 3268.0 | 3287.5 | 3232.0 |
| ICC | 0.20 | 0.20 | 0.20 |
| RMSE | 0.38 | 0.38 | 0.38 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

*Note:* Entries report linear probability models predicting alignment. Standard errors are in parentheses. The sample is restricted to rounds $t \geq 2$. All specifications include random intercepts for respondents. Alignment $_{t-1}$ denotes correct alignment in the previous round. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

### A.4.2 Context Scale Missing Data Sensitivity

Table A15: Context Scale: Missing Data Report by Racial Group

| **Group** | $N$ | **Included** | **Excluded** | **% Excluded** |
|---|---|---|---|---|
| Black | 189 | 143 | 46 | 24.3% |
| Multiracial | 153 | 116 | 37 | 24.2% |

*Note:* "Excluded" denotes respondents with fewer than two non-missing items on the contextual knowledge scale after coding "Racially balanced," "Mostly Hispanic," "Mostly Asian," and "Mostly Native American" responses as missing. Exclusion rates are approximately equal across groups (24.3% Black; 24.2% Multiracial).

Table A16: Context Mechanism: Alternative Context Scale (Balanced = 0.5)

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Intercept | 0.530*** | 0.440*** | 0.428*** |
| | (0.113) | (0.141) | (0.146) |
| Round | -0.028 | -0.028 | -0.028 |
| | (0.018) | (0.018) | (0.018) |
| Context Scale (Alt.) | -0.295* | -0.272 | -0.263 |
| | (0.176) | (0.176) | (0.178) |
| Multiracial | -0.268* | -0.263* | -0.248* |
| | (0.140) | (0.141) | (0.145) |
| Majority-Black District | 0.118*** | 0.121*** | 0.120*** |
| | (0.025) | (0.025) | (0.026) |
| Round × Context | 0.071** | 0.071** | 0.071** |
| | (0.028) | (0.028) | (0.028) |
| Round × Multiracial | 0.049** | 0.047** | 0.048** |
| | (0.022) | (0.022) | (0.023) |
| Context × Multiracial | 0.653*** | 0.654*** | 0.616** |
| | (0.241) | (0.241) | (0.249) |
| Round × Context × Multiracial | -0.116*** | -0.115*** | -0.117*** |
| | (0.039) | (0.039) | (0.039) |
| N | 1539 | 1521 | 1485 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

*Note:* Entries report linear probability models predicting alignment. Standard errors are in parentheses. The sample is restricted to the Uninformed condition and specifications include random intercepts by respondent. Alternative coding sets Mostly Black = 1, Mostly White = 0, and Balanced/Other = 0.5. Compare with Table 5 (original coding: Balanced/Other coded as missing). Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

### A.4.3 Ceiling Effects Diagnostic

Table A17: Alignment Rates by Racial Identity, Context Tercile, and Round Period (Uninformed Condition Only)

| **Context Tercile** | **Period** | $N$ | **Alignment** |
|---|---|---|---|
| **Black** | | | |
| Low | Rounds 1–3 | 12 | 41.7% |
| Low | Rounds 4–6 | 12 | 50.0% |
| Low | Rounds 7–9 | 12 | 36.1% |
| Medium | Rounds 1–3 | 29 | 44.8% |
| Medium | Rounds 4–6 | 29 | 35.6% |
| Medium | Rounds 7–9 | 29 | 48.3% |
| High | Rounds 1–3 | 29 | 34.5% |
| High | Rounds 4–6 | 29 | 48.3% |
| High | Rounds 7–9 | 29 | 59.8% |
| **Multiracial** | | | |
| Low | Rounds 1–3 | 32 | 34.4% |
| Low | Rounds 4–6 | 32 | 44.8% |
| Low | Rounds 7–9 | 32 | 39.6% |
| Medium | Rounds 1–3 | 17 | 54.9% |
| Medium | Rounds 4–6 | 17 | 51.0% |
| Medium | Rounds 7–9 | 17 | 39.2% |
| High | Rounds 1–3 | 13 | 53.8% |
| High | Rounds 4–6 | 13 | 56.4% |
| High | Rounds 7–9 | 13 | 41.0% |

*Note:* Context tercile cutpoints are Low $\leq 0.31$, Medium $\leq 0.80$, and High $> 0.80$. Alignment is the proportion of rounds in which respondents selected the correct community-policing position. The sample is restricted to the Uninformed condition, rounds 1–9.

Table A18: Quadratic Round Specification: Testing for Ceiling Effects

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Intercept | 0.413** | 0.275 | 0.255 |
| | (0.162) | (0.189) | (0.194) |
| Round | 0.008 | 0.005 | 0.006 |
| | (0.072) | (0.072) | (0.072) |
| Round$^2$ | -0.003 | -0.002 | -0.002 |
| | (0.007) | (0.007) | (0.007) |
| Context Scale | -0.247 | -0.235 | -0.226 |
| | (0.212) | (0.212) | (0.213) |
| Multiracial | -0.303 | -0.303 | -0.299 |
| | (0.193) | (0.195) | (0.198) |
| Majority-Black District | 0.123*** | 0.131*** | 0.128*** |
| | (0.032) | (0.032) | (0.033) |
| Round × Context | 0.068 | 0.068 | 0.068 |
| | (0.093) | (0.093) | (0.093) |
| Round$^2$ × Context | -0.001 | -0.001 | -0.001 |
| | (0.009) | (0.009) | (0.009) |
| Round × Multiracial | 0.114 | 0.109 | 0.113 |
| | (0.085) | (0.086) | (0.087) |
| Round$^2$ × Multiracial | -0.009 | -0.008 | -0.009 |
| | (0.008) | (0.008) | (0.008) |
| Context × Multiracial | 0.734** | 0.743*** | 0.689** |
| | (0.286) | (0.287) | (0.292) |
| Round × Context × Multiracial | -0.216* | -0.209* | -0.196 |
| | (0.126) | (0.126) | (0.128) |
| Round$^2$ × Context × Multiracial | 0.013 | 0.012 | 0.011 |
| | (0.012) | (0.012) | (0.012) |
| N | 1188 | 1179 | 1143 |
| Demographic Controls | | ✓ | |
| Full Controls | | | ✓ |

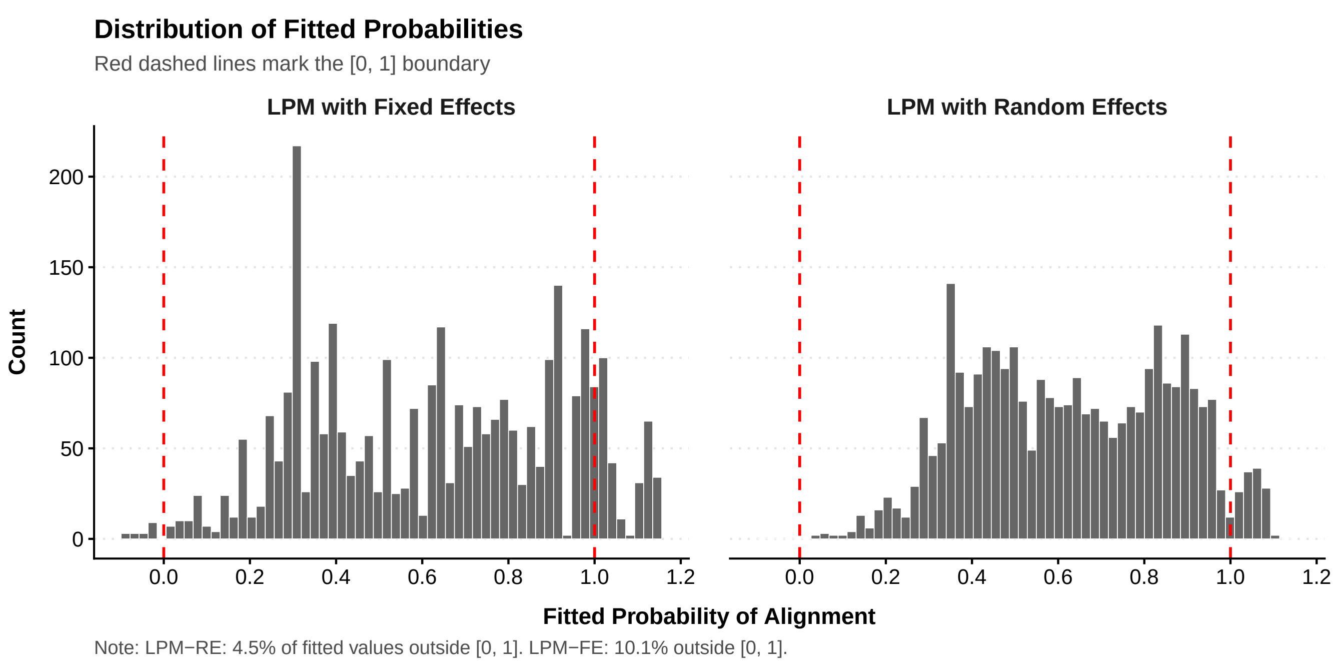
*Note:* Entries report linear probability models predicting alignment. Standard errors are in parentheses. The sample is restricted to the Uninformed condition and specifications include random intercepts by respondent. Non-significant quadratic terms indicate that ceiling effects do not drive the main results. Demographic controls include age, gender, income, and education; full controls additionally include party identification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

## A.5 Model Diagnostics

### A.5.1 Distribution of Fitted Probabilities

Figure A1 displays the distribution of fitted probabilities, with red dashed lines marking the admissible range of $[0, 1]$. This diagnostic assesses whether the linear probability model generates a substantial share of predicted values outside the unit interval, which would indicate potential misspecification of the functional form. The plots use fitted values from Model 3 in Table A6 and the corresponding mixed-effects specification. In both cases, only a small fraction of predictions fall outside the admissible range: 10.1% for the fixed-effects model and 4.5% for the random-effects model. These results suggest that violations of the unit-interval constraint are limited and that the linear probability specification provides a reasonable approximation. The mixed-effects model produces fewer out-of-bounds predictions and more closely adheres to the probability scale, offering additional support for its use in the main analyses.

Figure A1: Distribution of Fitted Probabilities




### A.5.2 Linear Interaction Effect Assumption

Hainmueller, Mummolo, and Xu (2019) show that the linear interaction effect (LIE) assumption can be violated when the relationship between the moderator and outcome is nonlinear, and that a lack of common support can cause interaction estimates to rely on extrapolation from sparse data. Figure A2 displays the distributions of both moderators—contextual knowledge and politicized racial identity—by group. There is common support across both scales, though the distributions differ in shape: the identity scale is left-skewed, with the majority of both Multiracial and Monoracial respondents scoring high, while the contextual knowledge scale shows greater separation, with Multiracial respondents concentrated at lower values and Monoracial respondents at higher values. Crucially, the overlapping regions of support are sufficient to identify the interaction effects without relying on extrapolation.

Hainmueller, Mummolo, and Xu (2019) also provide a diagnostic for the LIE assumption by binning the moderator and comparing nonparametric bin estimates to the parametric linear fit. Figures A3 and A4 present this diagnostic for contextual knowledge and politicized racial identity, respectively, with each moderator binned into terciles. In both cases, the binned estimates fall within the confidence interval of the linear parametric fit, indicating that the LIE assumption is not violated.

Figure A2: Common Support for Moderator Variables

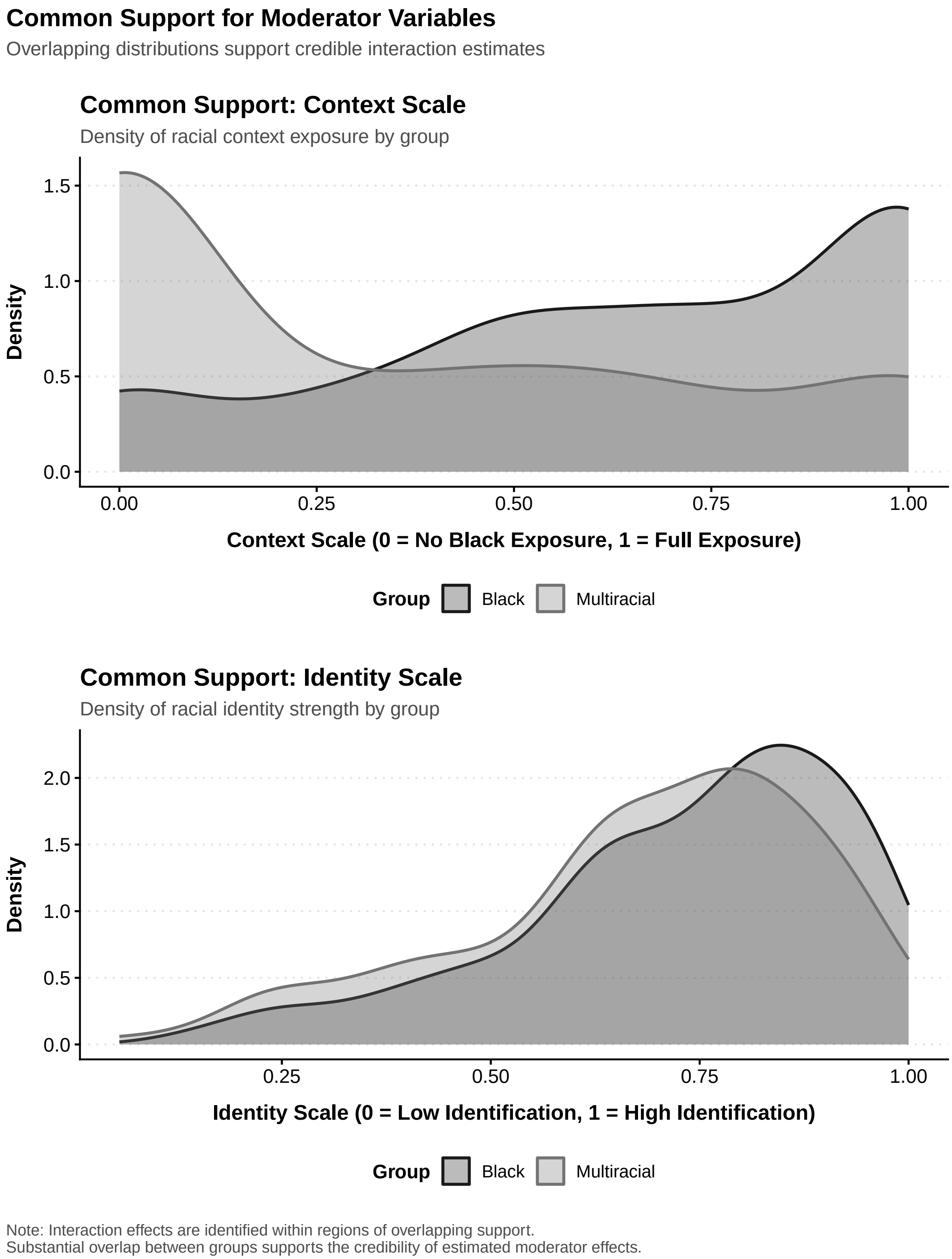


Figure A3: Linear Interaction Effect Assumption: Contextual Knowledge

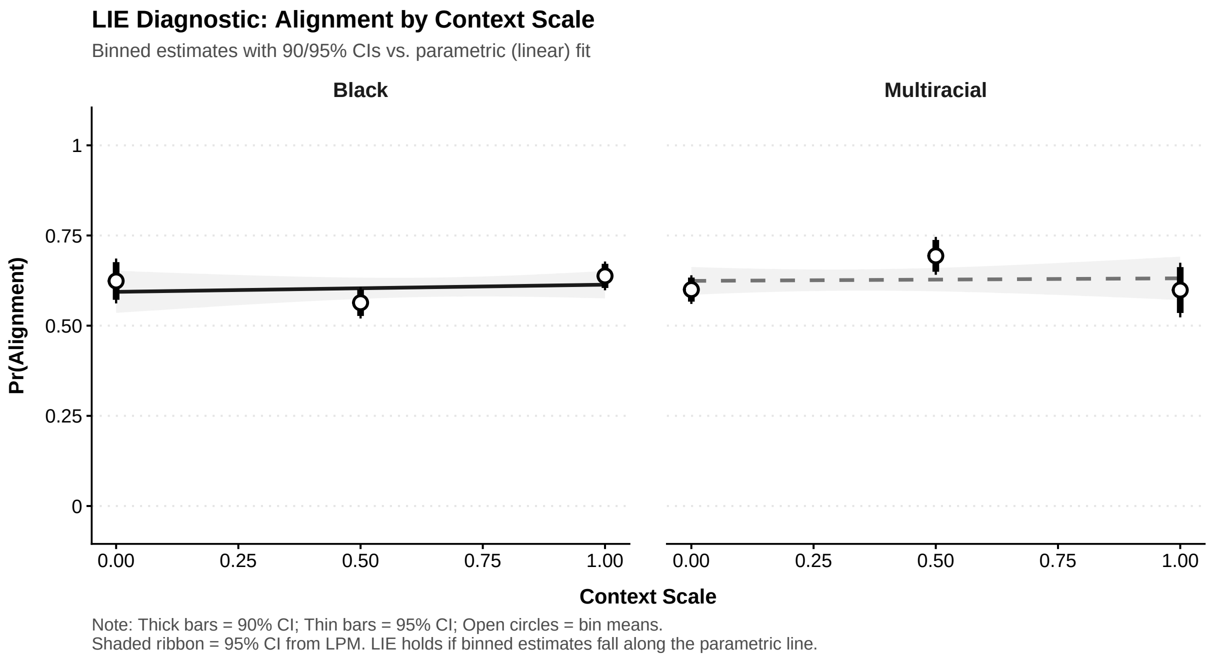
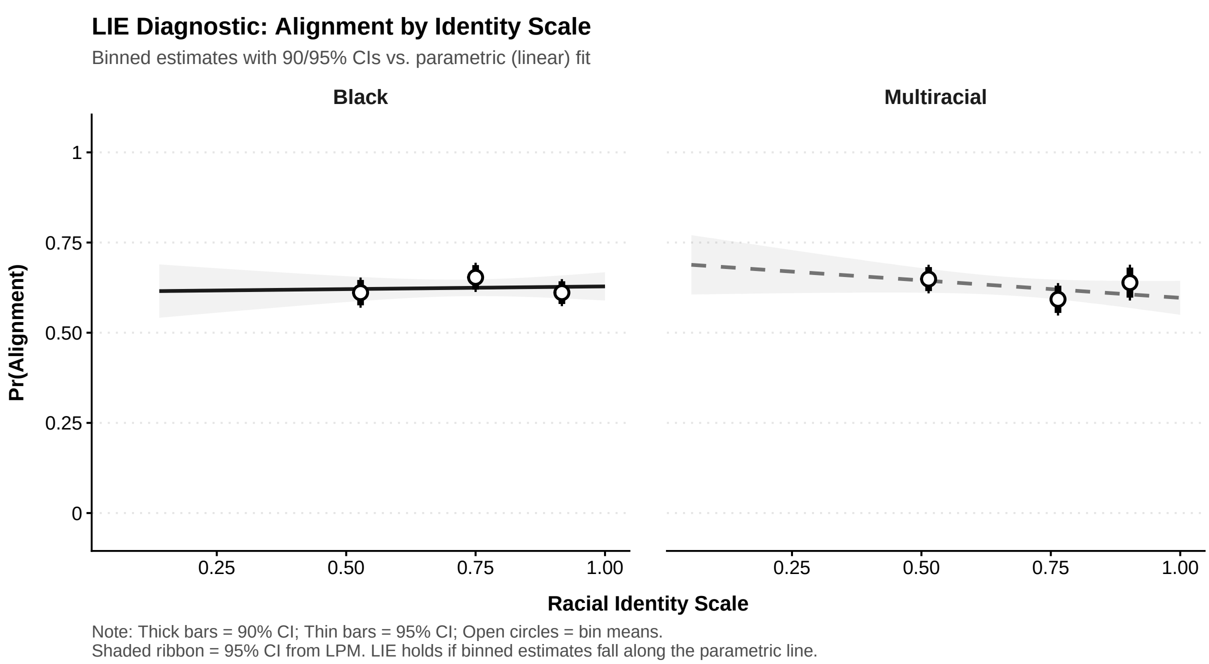



Figure A4: Linear Interaction Effect Assumption: Politicized Racial Identity



## A.6 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.6.1 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.[27] 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.

27. The religious services item is slightly different. See Table A19.

Table A19: 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 |

[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 (Religious Services)** 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.

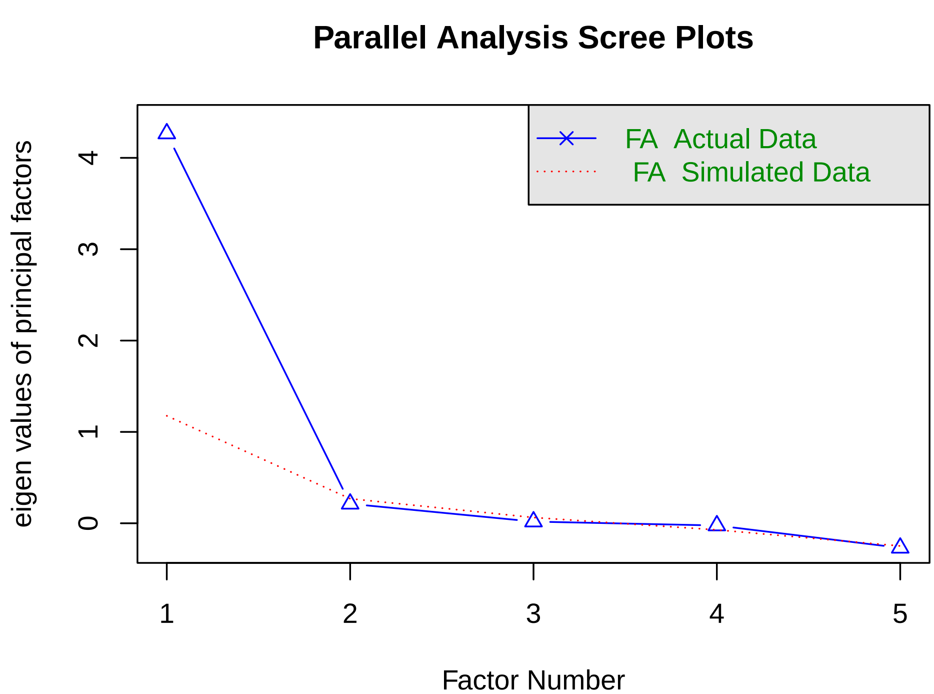
**Exploratory Factor Analysis.** Table A20 reports the exploratory factor analysis results for the contextual knowledge scale, including factor loadings, variance explained, and eigenvalues computed from the polychoric correlation matrix. All items load strongly onto a single latent factor, which accounts 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 A20: 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 A5: Parallel Analysis Scree Plot: Contextual Knowledge Scale



### A.6.2 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 A21: 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.7 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