The geography of the shooter bias: Regional context is linked to racialized threat perception

Abstract

The first-person shooter task is widely used for studying discrimination, grounded in theories linking shooter bias to threat-related stereotypes. Yet, evidence for these links remains weak. Using a large sample (N = 2,043) and a multilevel framework, we examined how individual and regional stereotypes and prejudice relate to shooter bias. Reaction time effects replicated robust shooter bias, but the unreliability of shooter bias measures limited individual-difference analyses. Correlations between individual stereotypes and prejudice with response bias for Black targets were small ($|r\text{s}|$ = .05-.10), yet detectable given high statistical power. Correlations with regional bias measures were stronger ($|r\text{s}|$ = .22-.34), magnifying effects through aggregation. Multilevel analyses revealed that regional bias predicted shooter bias beyond individual biases (contextual effects), and individual-level associations were amplified in high-bias regions (cross-level interactions). These findings underscore the value of regional approaches in revealing subtle psychological patterns and the influence of social context on discriminatory behavior.

Keywords: shooter bias, prejudice, stereotypes, regional bias

Word count: 4881

The geography of the shooter bias: Regional context is linked to racialized threat perception

Understanding the psychological underpinnings of discriminatory behavior remains a central challenge in social psychology. One widely used paradigm for studying discriminatory behavior is the first-person shooter task (Correll et al., 2002), which simulates real-time decision-making in potentially threatening scenarios. In this computer-based task, participants quickly decide whether to "shoot" armed or unarmed Black and White targets appearing in various street scenes. Three central findings emerge in the published literature using this task. First, participants apply a more lenient threshold when deciding to “shoot” Black versus White targets. Second, participants are faster to identify Black targets as armed. Third, participants more often mistakenly “shoot” unarmed Black targets. These effects – collectively referred to as shooter bias – are robust, with average effect sizes ranging from d = .11-.19 (Mekawi & Bresin, 2015), and even extend to other racialized groups (Essien et al., 2017).

Shooter bias is commonly attributed to cultural stereotypes that associate social groups with threat or danger (Payne & Correll, 2020). Correll et al. (2007a) provided experimental evidence that stereotypes linking Black people to danger can influence shoot/don’t-shoot decisions: exposure to media portraying Black individuals as criminals increased shooter bias. However, correlational evidence linking shooter bias with stereotypes and other self-reported intergroup bias measures is mixed (e.g., Correll et al., 2002; Correll et al., 2006; Correll et al., 2007b; Ito et al., 2015; Mekawi et al., 2016; Stelter et al., 2023). Meta-analytic evidence indicates a weak correlation (r = .08) between shooter bias and stereotype endorsement (Mekawi & Bresin, 2015). This inconsistency raises important questions about the psychological mechanisms underlying shooter bias.

Establishing clear links between shooter bias and other intergroup bias measures is essential for both scientific and practical reasons. Theoretically, stronger evidence connecting shooter bias and intergroup bias would help clarify the psychological mechanisms driving biased decision-making under uncertainty. Methodologically, such evidence would validate the first-person shooter task as a measure of bias, especially given its widespread use and psychological realism. Practically, understanding links between shooter bias and self-reported intergroup bias can inform targeted interventions to reduce discriminatory behavior.

To date, research linking shooter bias and self-reported intergroup bias has focused almost exclusively on individual-level predictors of shooter bias. However, intergroup bias can also be conceptualized as a characteristic of regions (Hehman et al., 2019). Regional differences in racial bias have been linked to a wide range of discriminatory outcomes for Black Americans, including harsher school discipline (Riddle & Sinclair, 2019), increased police stops (Stelter et al., 2022), and higher rates of fatal police violence (Hehman et al., 2018).

Importantly, correlations between intergroup bias and discriminatory outcomes tend to be stronger at the regional level (Payne et al., 2017) than at the individual level (Greenwald et al., 2009). Stronger regional-level correlations may result from aggregation, which reduces random error and improves reliability (Connor & Evers, 2020). Beyond statistical benefits, aggregation also filters out idiosyncratic variation, amplifying shared norms, beliefs, and psychological traits within a region – revealing a “true signal” that may be obscured by noise at the individual level (Calanchini et al., 2022). These shared features reflect broader social environments rather than just the sum of individual biases. For instance, local media and cultural norms may make stereotype-related concepts more cognitively accessible (Payne et al., 2017), increasing the likelihood of discriminatory behavior – even among individuals with relatively unbiased personal attitudes.

Leveraging regional analysis provides a useful tool to deepen our understanding of shooter bias and its relationship with other forms of intergroup bias. Regional aggregation reduces measurement error – especially for tasks known to have low reliability, like the first-person shooter task (Payne & Correll, 2020) – and captures the influence of shared social contexts. Analyzing shooter bias at the regional level thus offers a promising approach to understanding how shooter bias is linked to other forms of biases.

Extending previous regional bias research, this study employs a multilevel approach, which allows us to integrate individual psychology with regional context. By examining individual and regional levels simultaneously, we provide a clearer understanding of how shooter bias relates to other forms of intergroup bias. First, multilevel modeling enables us to assess whether regional bias predicts shooter bias beyond individual bias (i.e., contextual effects; Blalock, 1984; Christ et al., 2014). In high-bias regions, individuals may discriminate more – not necessarily due to personal beliefs, but because the environment encourages such behavior. Second, multilevel models allow us to explore cross-level interactions, revealing how regional norms shape individual-level associations. For example, people may suppress bias in regions with strong anti-discrimination norms, obscuring correlations between shooter bias and self-reported bias (Glaser & Knowles, 2008). These dynamics are often missed in individual-level or aggregate analyses but become visible through multilevel modeling.

Study Overview

Although shooter bias is well-documented, its psychological underpinnings and sensitivity to social context remain poorly understood. This study addresses these gaps by leveraging large-scale data to examine how shooter bias relates to both individual bias and the geographic contexts in which individuals are embedded. We recruited over 2,000 participants – the largest sample in shooter bias research to date – from 100 distinct U.S. regions. This regional sampling allowed us to capture meaningful variation in regions and assess how local context is linked to biased decision-making.

To assess self-reported intergroup bias, we used a multi-method approach capturing both stereotypes and prejudice. Whereas shooter bias research has emphasized stereotypes as a major explaining factor, regional bias studies show that aggregated prejudice strongly predicts discriminatory outcomes (e.g., Stelter et al., 2022). Our self-report measures included associations between Black and White individuals and weapons (Xu et al., 2017), perceived threat from Black or White faces (Oosterhof & Todorov, 2008), the perceived legitimacy of using racial stereotypes (Bayesian racism; Litam & Balkin, 2021), and group preference ratings (Xu et al., 2017).

Finally, we examined shooter bias in relation to structural regional factors often overlooked in individual-level research – such as racial demographics, residential segregation, gun laws, gun sales, income inequality, disproportionate police killings of Black residents, and hate crime frequency – to further contextualize shooter bias within broader sociocultural environments.

Methods

Research Transparency Statement

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. This research was approved by the Ethics Committee of [UNIVERSITY NAME]. Data collection procedure, hypotheses and analytic approach were preregistered at https://osf.io/a7xpu/?view_only=d48927c2fda64828be4ec7297941a1f0. Study materials are publicly available at https://osf.io/r7fmt/?view_only=555e0c0a9cc94d1a9e62f80cc1b8ccda. Data and analysis script are publicly available at https://osf.io/r7fmt/?view_only=555e0c0a9cc94d1a9e62f80cc1b8ccda.

Participants

Our target sample size was $N = 2{,}000$ White participants residing in 100 predefined U.S. core-based statistical areas (CBSAs), with a goal of recruiting $n = 20$ participants per CBSA. This level-1 sample size provides sufficient power to detect small individual-level correlations. At level 2, the inclusion of 100 CBSAs exceeds recommended thresholds for reliable multilevel regression estimates (Hox & McNeish, 2020), and a minimum of 20 participants per CBSA allows for examining regional–individual associations (Schunck, 2016).

Participants were recruited via Prolific using a multi-step strategy. We first selected the 40 U.S. states with the highest number of White Prolific users and conducted a screening survey to collect location data (i.e., county, which we mapped to CBSA) from $N = 11{,}191$ self-identified White participants. We then invited individuals from CBSAs with at least 20 responses, resulting in a final sample of $N = 2{,}043$ participants (Md age = 39 [range: 18–86]; 1,000 women, 966 men, 76 diverse/other gender, 1 not reported), all residing in one of the 100 target CBSAs ($M = 20.55$ [range: 15-24] participants per CBSA). We excluded 13 participants who reported inconsistent CBSA locations between the screening and main study (see Supplement for details).

Measures

First-person shooter task

The first-person shooter task, based on Correll et al. (2007b) and programmed in PsychoPy (Morys-Carter, 2023), included 16 practice and 100 test trials. Each trial presented armed or unarmed Black or White targets (25 per condition) on randomized backgrounds. Participants were instructed to decide quickly if a target was armed or not. The response window was set to 850 ms and participants received feedback on each trial whether their response was correct, incorrect, or too slow. Participants received points according to the same payoff matrix as used by Correll et al. (2007). Key dependent variables of the shooter task are reaction times for correct responses, error rates, and signal detection parameter *c* (response bias). We also explored effects in parameter *d'* (discrimination accuracy).

Exemplar-based threat ratings

Participants rated 14 male faces (7 Black, 7 White) from the Chicago Face Database (Ma et al., 2015) on perceived threat (1 = not at all threatening, 7 = very threatening). Images were selected based on highest prototypicality ratings for each group and presented individually in random order. Ratings showed high internal consistency for both Black (Ω = .90) and White (Ω = .87) faces.

Stereotype measure

We adapted the stereotype measure from Project Implicit (Xu et al., 2017). Participants rated their associations of weapons and harmless objects with Black vs. White Americans on a 7-point scale (1 = "strongly with Black people", 4 "Neither Black nor White", 7 = "strongly with White people"). Items were recoded such that higher scores reflect stronger associations with Black people.

Group preference

We adapted the group preference measure from Project Implicit (Xu et al., 2017). Participants selected one of seven statements indicating their preference for White vs. Black Americans, ranging from 1 = "strongly prefer Black people" to 7 = "strongly prefer White people".

Bayesian racism

The Bayesian Racism scale (Litam & Balkin, 2021) includes six items assessing the belief that using racial stereotypes is reasonable (e.g., "You should use a person's ethnic group to predict performance"). Participants rated agreement on a 7-point scale (1 = strongly disagree, 7 = strongly agree). The scale showed good internal consistency (Ω = .84).

Demographics

Participants reported their age, gender, race, time regularly spent with video games, and county of residence.

Procedure

Participants provided consent and then completed the shooter task hosted on Pavlovia. After completing the shooter task, participants were redirected to Qualtrics and completed the exemplar-based threat rating, the stereotype measure, the group preference measure, the Bayesian Racism scale, and provided demographic information. At the end of the study, participants were fully debriefed about the study aims and provided consent to include their data for analysis and publication.

Results

Preliminary analyses of self-reported intergroup biases and shooter bias

Exemplar-based threat rating

On average, participants rated the Black exemplars (M = 3.22, SD = 1.12) as less threatening than the White exemplars (M = 3.32, SD = 1.07), $\boldsymbol{t(2,042) = -4.31}$, $\boldsymbol{p < .001}$, d_z = -0.10, 95% CI [-0.14; -0.05].

Stereotype measure

Participants associated both weapons, M = 3.84, SD = 1.31, t(2,042)=-5.51, p <.001, d_z = -0.12, 95% CI [-0.17; -0.08], and harmless objects, M = 3.85, SD = 0.64, t(2,042)=10.68, p <.001, d_z = 0.24, 95% CI [0.19; 0.28], more strongly with White people than with Black people, as indicated by values lower than the scale midpoint of 4. The difference between both items was not significant, M_D = 0.01, 95% CI [-0.06,0.08], t(2,042) = 0.25, p = .806.

Group preference

Group preference ratings were on average above the scale midpoint of 4, $M = 4.34$, $SD = 0.86$, $t(2{,}041) = 17.82$, $p < .001$, $d_z = 0.39$, 95% CI [0.35; 0.44], indicating that participants preferred White over Black people.

Bayesian racism

On average, participants disagreed with statements of the Bayesian Racism scale, as indicated by scores below the scale midpoint of 4, $M = 2.75$, $SD = 1.27$, $t(2034) = -44.30$, $p < .001$, $dz = -0.98$, 95% CI [-1.03; -0.93].

First-person shooter task

Shooter task responses were classified as hits ("gun" response to armed targets) and false alarms ("gun" response to unarmed targets). We calculated response bias *c* using hit and false alarm rates ($c = (-0.5 \times (z \text{ hits} + z \text{ false alarms}))$). Hit rates = 1 were replaced by 1 - 1/(2 * number of trials) and false alarm rates = 0 were replaced by 0 + 1/(2 * number of trials) to avoid infinite *z*-values (Macmillan & Creelman, 2004). For each participant, we computed average reaction times and error rates across the four conditions.

Figure 1 reflects the descriptive results. We analyzed reaction times and error rates in two 2 (Target group: Black, White) x 2 (Object Type: Gun, Object) ANOVAs with repeated measures on both factors. We report the results of both ANOVAs in Table 1.

Reaction times. A significant Target Group × Object Type interaction in reaction times indicated shooter bias. Participants responded faster to armed Black compared to armed White targets, $t(2{,}022) = -8.53$, $p < .001$, $d_z = -0.19$, 95% CI [-0.23; -0.15], but slower to unarmed Black compared to unarmed White targets, $t(2{,}013) = 11.96$, $p < .001$, $d_z = 0.27$, 95% CI [0.22; 0.31].

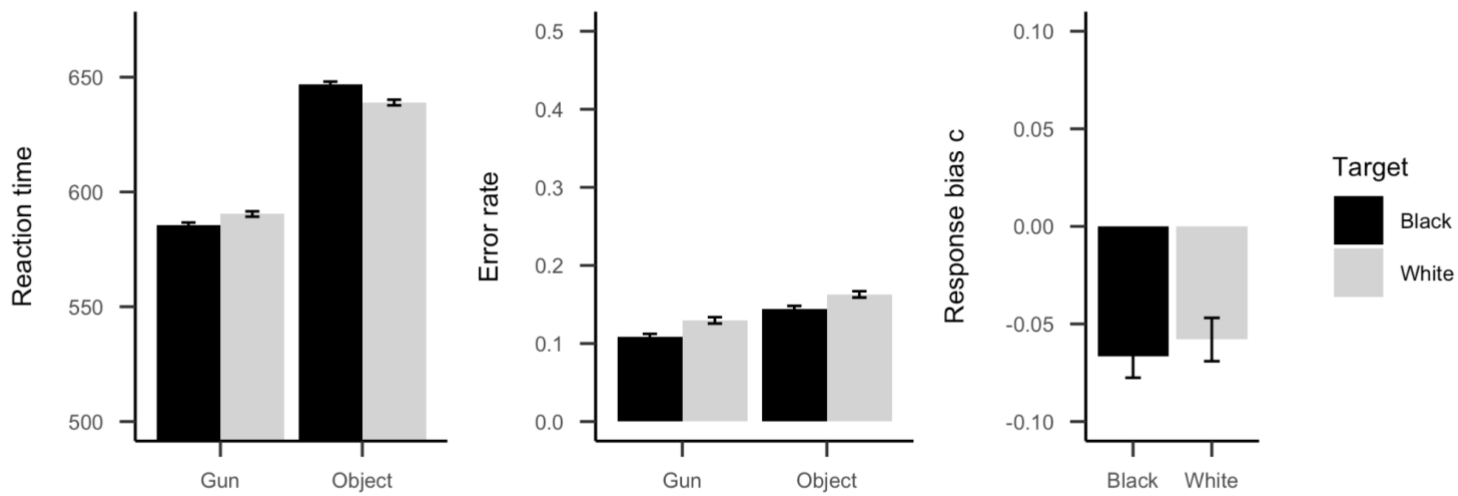
Table 1

ANOVA results for reaction times and error rates in the first-person shooter task.

	Reaction times						Error rates					
	η_p^2	90% CI	F	df_1	df_2	p	η_p^2	90% CI	F	df_1	df_2	p
Object	.679	[.663, .695]	4,265.96	1	2013	< .001	.070	[.053, .088]	151.29	1	2013	< .001
Target	.005	[.001, .011]	9.82	1	2013	.002	.088	[.069, .108]	194.10	1	2013	< .001
Object × Target	.098	[.078, .119]	218.10	1	2013	< .001	.000	[.000, .002]	0.30	1	2013	.587

Figure 1

Shooter biases in reaction times, error rates, and response biases.



Error rates. The Target Group × Object Type interaction in error rates was not significant, indicating no shooter bias in errors. However, participants made more errors for White than Black targets, both when targets were armed, $t(2{,}022) = 10.17$, $p < .001$, $d_z = 0.23$, 95% CI [0.18; 0.27], and unarmed $t(2{,}015) = 9.20$, $p < .001$, $d_z = 0.20$, 95% CI [0.16; 0.25].

Response bias *c*. No difference in response bias *c* emerged between Black and White targets, $t(2{,}031) = -1.06$, $p = .289$, $d_z = -0.02$, 95% CI [-0.07; 0.02]. However, *c* values were below zero for both Black, $M = -0.07$, $SD = -0.07$, $t(2{,}032) = -9.76$, $p < .001$, $d_z = -0.22$, 95% CI [-0.26; -0.17], and White targets, $M = -0.06$, $SD = -0.06$, $t(2{,}031) = -8.29$, $p < .001$, $d_z = -0.18$, 95% CI [-0.23; -0.14], indicating a general bias toward detecting weapons.

Signal detection parameter *d'*. Signal detection parameter *d*' was higher for Black, $M = 2.60$, $SD = 2.60$, compared to White targets, $M = 2.38$, $SD = 2.38$, $t(2{,}031) = 14.92$, $p < .001$, $d_z = 0.33$, 95% CI [0.29; 0.38], indicating that participants made more accurate responses for Black than White targets.

Reliability of shooter bias indices. We computed shooter bias indices using difference scores:

Reaction times:

$$(\text{reaction time}_{\text{Object/Black}} - \text{reaction time}_{\text{Object/White}}) + (\text{reaction time}_{\text{Gun/White}} - \text{reaction time}_{\text{Gun/Black}})$$

Error rates:

$$(\text{error rate}_{\text{Object/Black}} - \text{error rate}_{\text{Object/White}}) + (\text{error rate}_{\text{Gun/White}} - \text{error rate}_{\text{Gun/Black}})$$

Response bias *c*: $c_{\text{White}} - c_{\text{Black}}$.

We estimated split-half reliabilities for shooter bias indices using a bootstrap procedure (1,000 repetitions), randomly splitting stimuli within each condition and computing Spearman-Brown corrected correlations $[2 * r / (1 + |r|)]$. Reliability was assessed at both the individual level (splitting trials within participants) and regional level (aggregating responses by CBSA before splitting).

Figure 2 shows split-half correlations for shooter bias indices at the individual level. As shown in Table 2, reliabilities for bias scores in reaction times, error rates, and response bias *c* were near zero at both individual and regional levels. Only separate *c* values for Black and White targets showed moderate reliability (*r*s = .32–.44).

Figure 2

Individual-level split-half correlations of shooter bias indices in reaction times, error rates and response bias c.

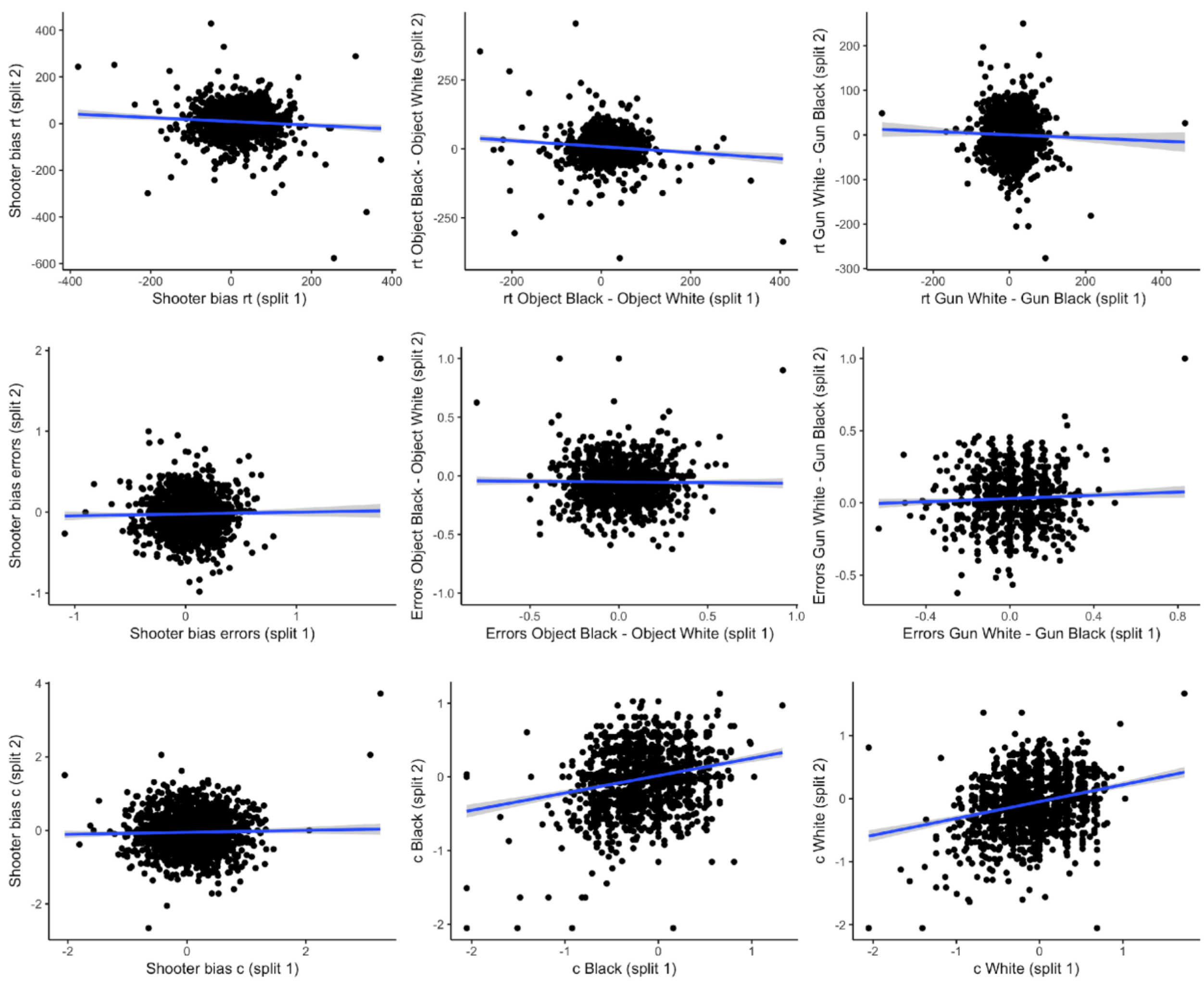


Table 2

Split-half reliabilities and 95% confidence intervals for shooter bias indices at individual and regional levels.

Shooter bias indices	Individual level	Regional level
Reaction times: Object Type x Target Group interaction	-0.05 [-0.17, 0.06]	0.08 [-0.19, 0.32]
Reaction times: Gun/White - Gun/Black	-0.06 [-0.17, 0.04]	0.02 [-0.23, 0.29]
Reaction times: Object/Black - Object/White	-0.06 [-0.19, 0.08]	-0.06 [-0.19, 0.08]
Error rates: Object Type x Target Group interaction	0.02 [-0.06, 0.10]	0.08 [-0.17, 0.30]
Error rates: Gun/White - Gun/Black	0.03 [-0.06, 0.10]	0.17 [-0.08, 0.39]
Error rates: Object/Black - Object/White	-0.04 [-0.13, 0.05]	-0.04 [-0.13, 0.05]
Response bias c: White - Black	0.02 [-0.07, 0.10]	0.05 [-0.19, 0.29]
Response bias c: Black	0.37 [0.32, 0.41]	0.44 [0.26, 0.58]
Response bias c: White	0.40 [0.36, 0.44]	0.32 [0.11, 0.50]

Individual-level correlations between shooter biases and self-reported intergroup bias

To isolate individual-level effects, we adjusted values by subtracting each participant's CBSA mean. We applied this procedure to each variable. Table 3 reports correlations between shooter bias indices and self-reported intergroup bias measures.

Response bias c for Black targets was negatively related to threat-perceptions of Black individuals (r = -.10, t(2,031) = -4.40, p = <.001; r = -.08 when controlling for c for White targets), associations of Black people with weapons (r = -.05, t(2,031) = -2.29, p = .022; r = -0.03, n.s., when controlling for c for White targets), group preference (r = -.07, t(2,030) = -3.10, p = .002; r = -0.06 when controlling for c for White targets), and Bayesian racism (r = -.07, t(2,031) = -3.21, p = .001; r = -.07 when controlling for c for White targets), suggesting that higher levels of prejudice and stereotypes was linked to a greater tendency to perceive Black targets as armed. In contrast, shooter bias indices based on reaction times and error rates showed no significant correlations with intergroup bias.

In summary, participants showed a consistent shooter bias in reaction times, but this bias was unrelated to individual prejudice and stereotypes. However, individual differences in response bias *c* for Black targets were modestly linked to stereotype and prejudice measures (see Figure 3).

Figure 3

Participants displayed shooter biases in reaction times regardless of their threat perception (left panel); in contrast, response bias c varied with threat perception, showing greater bias against Black targets as perceived threat increased (right panel).

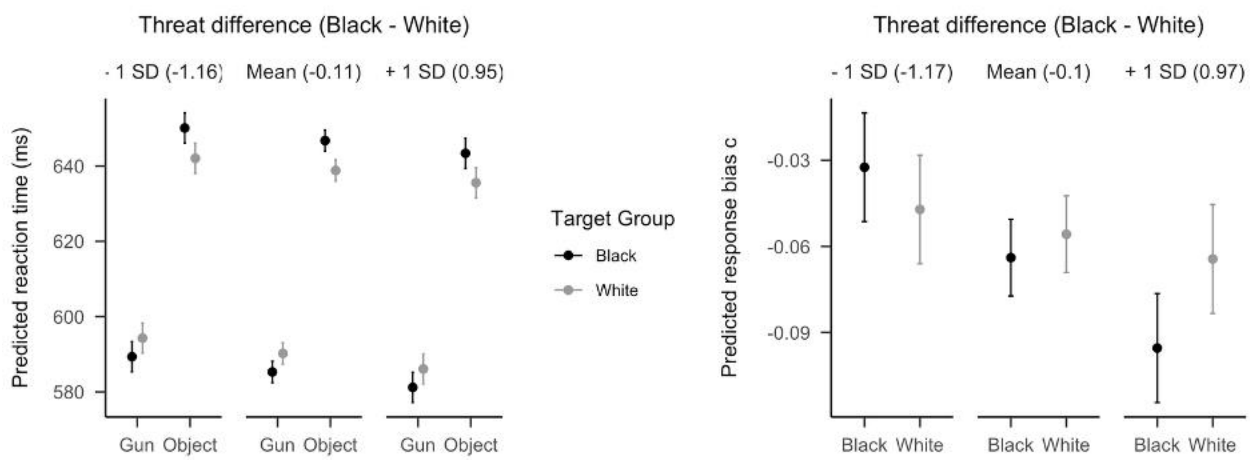


Table 3

Individual-level correlations between shooter bias indices and self-reported intergroup bias measures.

	1	2	3	4	5	6	7	8	9	10	11	12
1. Shooter bias in reaction-times	-											
2. Shooter bias in errors	-.04*	-										
3. Shooter bias in response bias *c*	-.06*	.92***	-									
4. *c* Black	.07**	-.48***	-.56***	-								
5. *c* White	.00	.58***	.60***	.33***	-							
6. *d'* Black	.11***	-.02	-.03	.30***	.27***	-						
7. *d'* White	.12***	-.01	.00	.27***	.26***	.77***	-					
8. Preference	-.04	.01	.03	-.07**	-.04	-.01	-.01	-				
9. Weapons-Black association	-.02	-.02	-.01	-.05*	-.06**	-.04	-.04	.37***	-			
10. Harmless-White association	.00	-.04	-.02	-.03	-.06**	-.04	-.03	.34***	.30***	-		
11. Threat Black	-.03	-.02	.02	-.10***	-.07**	-.07**	-.06**	.36***	.29***	.23***	-	
12. Threat White	-.03	-.01	-.03	-.02	-.05*	-.04	-.05*	-.08***	-.12***	-.07**	.53***	-
13. Bayesian racism	-.02	.03	.04*	-.07**	-.02	-.02	-.01	.53***	.34***	.28***	.44***	.04*

Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Regional-level correlations between shooter biases and self-reported intergroup bias

We computed regional-level correlations using CBSA-aggregated values. Figure 5 maps aggregated shooter biases and threat perceptions, and Table 4 summarizes regional-level correlations. Response bias *c* for Black targets was significantly associated with higher regional levels of threat perceptions of Black individuals (r = - .34, $t(98) = -3.54$, $p < .001$; r = - .33 when controlling for *c* for White targets), preference for White people ($r = -.32$, $t(98) = -3.33$, $p = .001$; $r = -.28$ when controlling for *c* for White targets), and Bayesian racism ($r = -.22$, $t(98) = -2.24$, $p = .027$; $r = -.21$ when controlling for *c* for White targets). Shooter bias indices based on reaction times and error rates showed no regional-level associations with intergroup bias.

Overall, regional patterns mirrored individual-level findings, with stronger associations for *c* at the regional level (*r*s = –.22 to –.34) than at the individual level (*r*s = –.05 to –.10).

Figure 4

Correlations between response bias c for Black targets and perceptions of threat of Black individuals, preference for White over Black people, and Bayesian racism are larger at the regional level (lower panel) than at the individual level (upper panel).

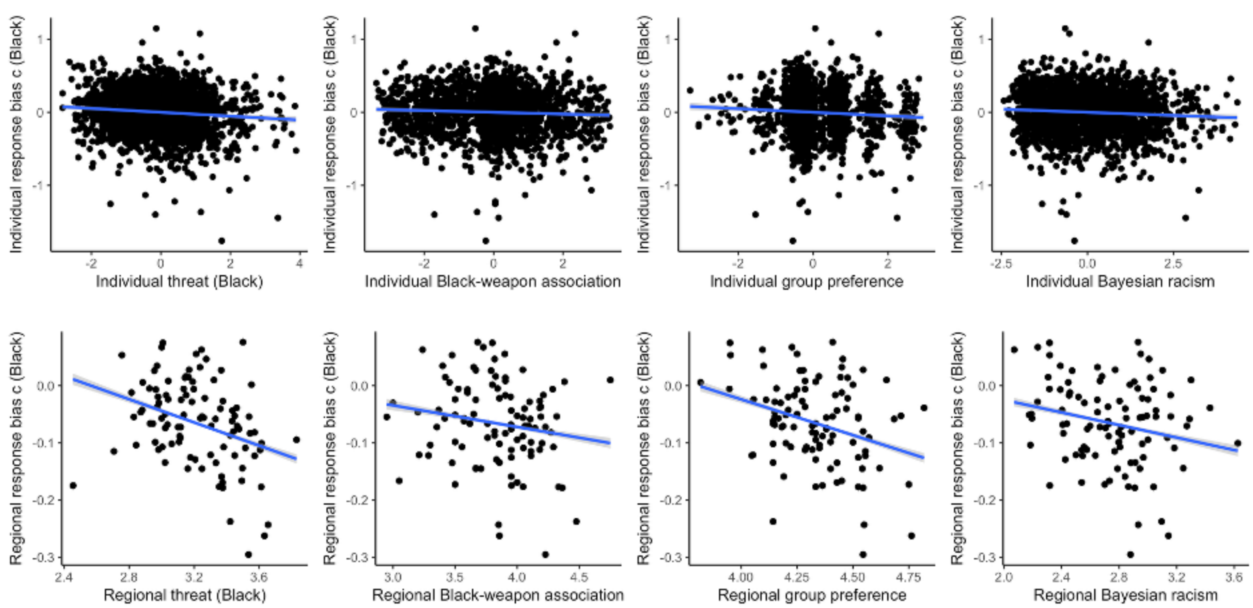


Figure 5

The top map illustrates regional variation in response bias c toward Black targets in the first-person shooter task. Values below zero indicate a tendency to mistakenly identify objects as weapons. The bottom map displays regional variation in perceived threat from Black faces. Higher values correspond with stronger threat perceptions.

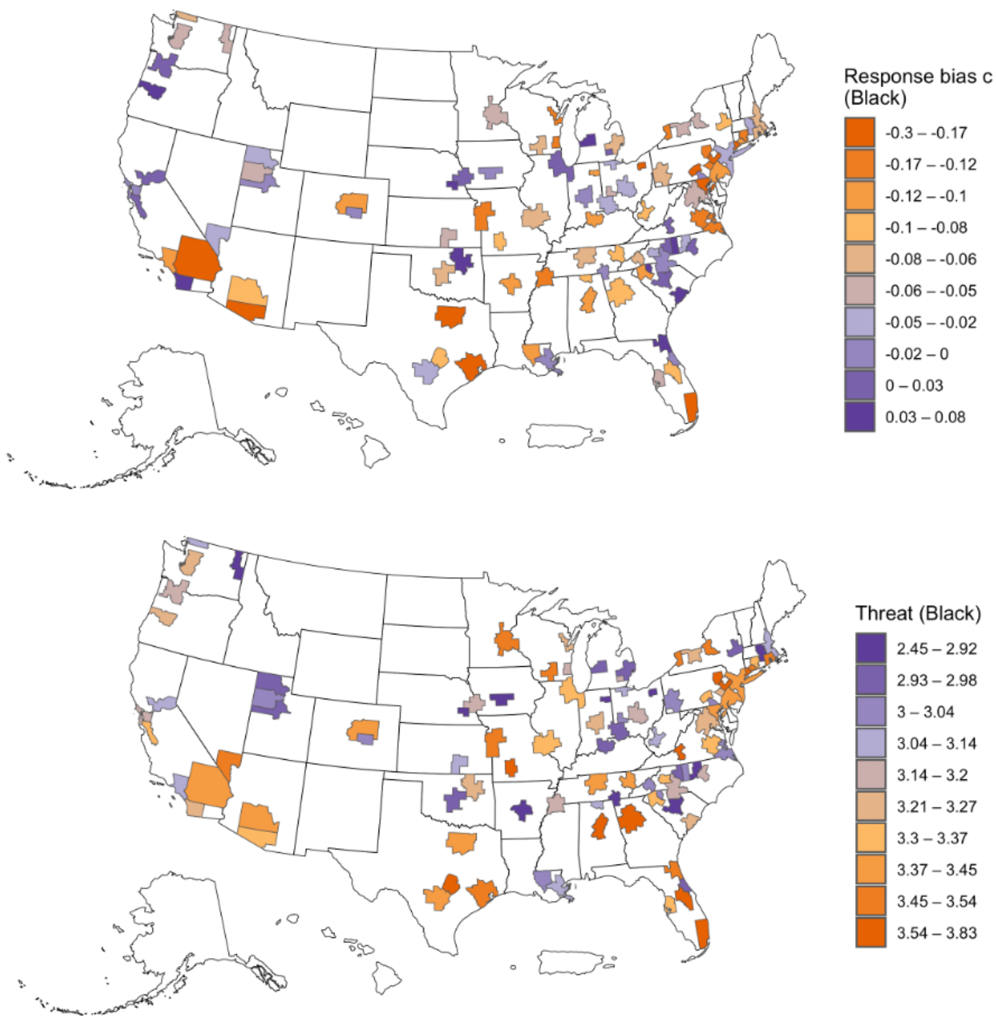


Table 4

Regional-level correlations between shooter bias indices, self-reported intergroup bias, and structural characteristics of the regions.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Shooter bias in reaction-times	-															
2. Shooter bias in errors	.09	-														
3. Shooter bias in response bias c	.04	.81***	-													
4. *c* Black	.01	-.49***	-.60***	-												
5. *c* White	.05	.46***	.57***	.31**	-											
6. *d'* Black	.23*	.00	-.13	.41***	.27**	-										
7. *d'* White	.08	-.04	-.12	.41***	.28**	.75***	-									
8. Preference	-.01	.13	.13	-.32**	-.17	-.17	-.19	-								
9. Weapons-Black	-.04	.05	.05	-.16	-.11	-.12	-.06	.36***	-							
10. Harmless-White	-.08	.03	-.01	-.02	-.03	.02	.05	.41***	.45***	-						
11. Threat Black	-.03	.15	.22*	-.34***	-.07	-.18	-.24*	.40***	.32**	.25*	-					
12. Threat White	-.03	.00	-.02	.04	.01	-.07	-.12	-.22*	-.27**	-.19	.40***	-				
13. Bayesian racism	.09	.09	.11	-.22*	-.08	-.02	-.16	.49***	.45***	.36***	.49***	-.06	-			
14. % White population	-.08	.00	-.04	.10	.05	.04	-.07	-.09	-.28**	-.18	-.24*	-.02	-.36***	-		
15. Racial segregation	-.21*	-.15	-.04	-.23*	-.27**	-.32**	-.19	.02	.27**	-.02	.03	-.04	-.03	-.06	-	
16. Violent crime rate	-.06	-.04	-.05	-.03	-.10	-.15	-.03	-.05	-.20	-.04	-.12	.07	-.04	-.29**	.09	-
17. Income inequality	.01	-.06	.10	-.13	.01	-.28**	-.21*	.15	.22*	.14	.23*	.11	.20*	-.45***	.40***	.28**

Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Multilevel analyses

Following separate individual- and regional-level analyses, we ran multilevel regression models to examine the interplay of individual and regional effects. As a preliminary step, we calculated intra-class correlations (ICCs) to assess between-region variability in shooter bias and intergroup bias measures.

Variability of shooter biases and self-reported intergroup biases between regions

To assess regional variability in shooter bias, prejudice, and stereotypes, we computed ICCs, which reflect the proportion of variance explained by regions. ICCs close to 1 indicate strong regional clustering; values near 0 suggest minimal regional variation.

All ICCs were low, including shooter bias in reaction times and errors (< .001), response bias *c* (Black: .013; White: .005), and self-reported bias measures (group preference: .001; stereotypes associated with weapons: .019; stereotypes associated with harmless objects: .023, threat ratings of Black individuals: 0.002; threat ratings of White individuals: .003; Bayesian racism: 0.011), indicating that regional differences accounted for only 1–2% of total variance.

Contextual effects: Are shooter biases linked to regional bias beyond individual bias?

We conducted multilevel regressions predicting response bias *c* for Black targets from both individual and regional self-reported biases, controlling for *c* for White targets. Analyses of shooter bias difference scores are reported in the Supplement (Tables S2–S4) due to their low reliability and lack of correlations with self-report measures. Contextual effects were assessed by comparing regional and individual regression coefficients using *t*-tests (Paternoster et al., 1998). If the regional coefficient is significantly larger than the individual coefficient, it implies that people's response bias in the shooter task depends on regional levels of bias, not just their personal bias.

Table 5

Multi-level regression models separating effects of individual versus regional bias and assessing cross-level interactions between individual and regional bias on response bias c for Black targets (controlling for response bias c for White targets) in the shooter task.

	Individual vs. regional effects					Cross-level interactions				
	$\hat{\beta}$	95% CI	t	df	p	$\hat{\beta}$	95% CI	t	df	p
Intercept	-0.06	[-0.07, -0.04]	-7.72	105.53	< .001	-0.06	[-0.07, -0.04]	-7.71	105.51	< .001
Response bias *c* White	0.31	[0.27, 0.35]	15.46	2027.58	< .001	0.31	[0.27, 0.35]	15.55	2026.55	< .001
Threat Black-White (individual)	-0.02	[-0.03, -0.01]	-3.66	1934.29	< .001	-0.03	[-0.04, -0.01]	-4.08	1933.17	< .001
Threat Black-White (regional)	-0.09	[-0.14, -0.04]	-3.47	99.84	< .001	-0.09	[-0.14, -0.04]	-3.46	99.84	< .001
Threat Black-White (individual x regional)						-0.05	[-0.09, -0.01]	-2.55	1932.92	.011
Intercept	0.06	[-0.10, 0.22]	0.76	102.63	.447	0.06	[-0.10, 0.22]	0.76	102.62	.448
Response bias *c* White	0.31	[0.27, 0.35]	15.38	2025.84	< .001	0.31	[0.27, 0.35]	15.39	2024.78	< .001
Black-weapons (individual)	-0.01	[-0.02, 0.00]	-1.58	1935.30	.115	0.12	[0.01, 0.23]	2.19	1932.99	.028
Black-weapons (regional)	-0.03	[-0.07, 0.01]	-1.36	102.27	.177	-0.03	[-0.07, 0.01]	-1.36	102.26	.178
Black-weapons (individual x regional)						-0.03	[-0.06, -0.01]	-2.35	1932.96	.019
Intercept	-0.40	[0.09, 0.72]	2.51	100.82	.014	0.40	[0.09, 0.72]	2.51	100.83	.014
Response bias *c* White	0.31	[0.27, 0.35]	15.36	2025.66	< .001	0.31	[0.27, 0.35]	15.41	2024.62	< .001
Group preference (individual)	-0.02	[-0.04, -0.01]	-2.83	1934.52	.005	0.38	[0.03, 0.72]	2.14	1933.20	.032
Group preference (regional)	-0.10	[-0.18, -0.03]	-2.81	100.78	.006	-0.10	[-0.18, -0.03]	-2.81	100.79	.006
Group preference (individual x regional)						-0.09	[-0.17, -0.01]	-2.27	1933.11	.023
Intercept	0.07	[-0.05, 0.20]	1.15	101.31	.252	0.07	[-0.05, 0.20]	1.15	101.31	.252
Response bias *c* White	0.31	[0.27, 0.35]	15.48	2026.11	< .001	0.31	[0.27, 0.35]	15.47	2025.09	< .001
Bayesian racism (individual)	-0.02	[-0.03, -0.01]	-3.03	1934.18	.002	0.04	[-0.06, 0.13]	0.76	1933.02	.447
Bayesian racism (regional)	-0.04	[-0.09, 0.00]	-1.92	101.35	.058	-0.04	[-0.09, 0.00]	-1.92	101.34	.058
Bayesian racism (individual x regional)						-0.02	[-0.05, 0.02]	-1.08	1933.03	.279

Table 5 presents the results of the multilevel regressions. Regional threat perceptions and group preference were significantly stronger predictors of response bias *c* to Black targets than individual-level measures ($\beta_{regional} - \beta_{individual} = .07$, $t(2,026) = 2.52$, $p = .012$, and $\beta_{regional} - \beta_{individual} = .08$, $t(2,025) = 2.18$, $p = .029$, respectively). These findings suggest contextual effects: participants were more likely to perceive Black targets as armed in regions characterized by stronger threat perceptions and stronger preferences for White over Black individuals – independent of personal biases. No contextual effects emerged for other variables (*ps* > .22).

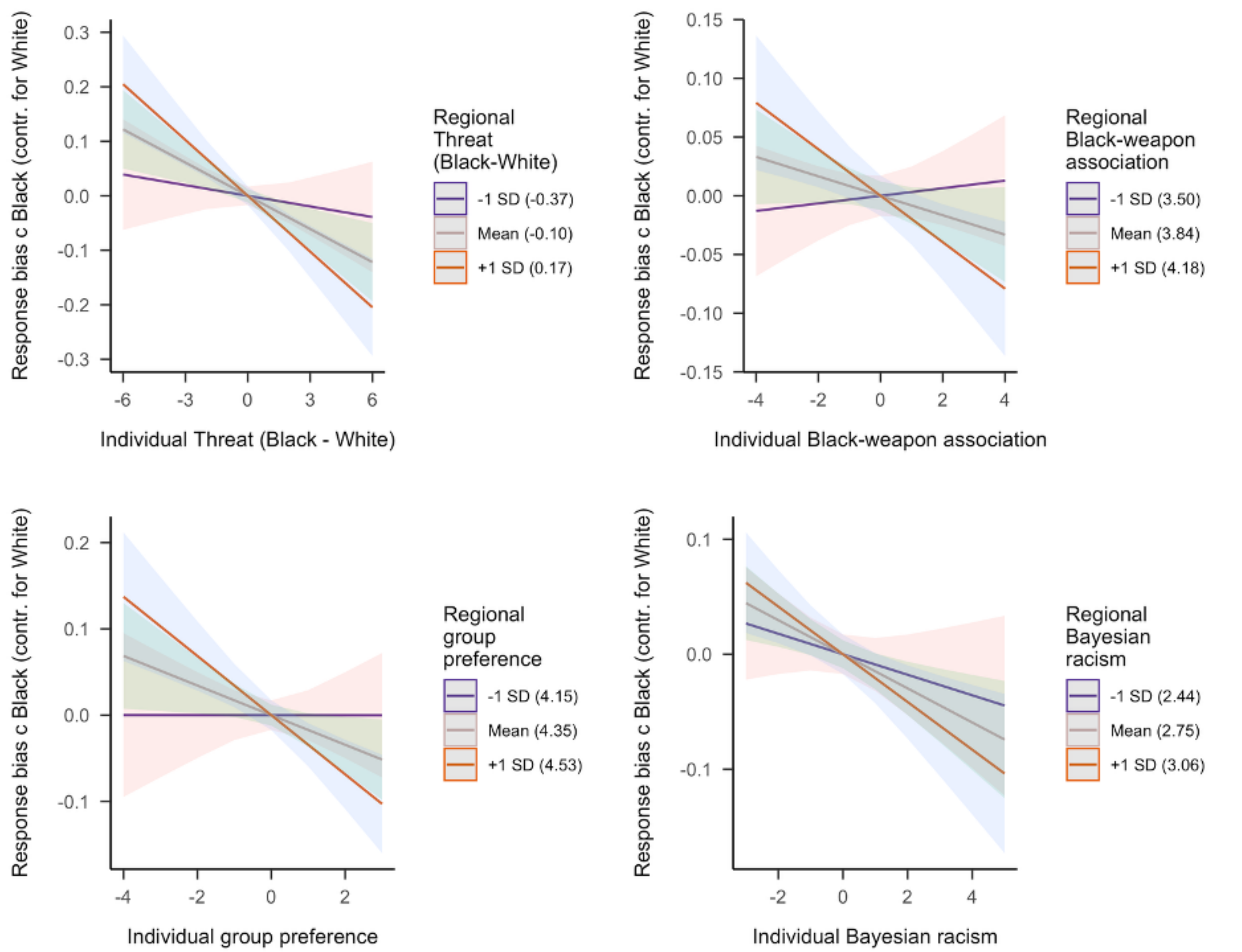
Cross-level interactions: To what extent do individual-level correlations between shooter bias and self-reported intergroup biases vary as a function of regional bias?

We used multilevel regressions to test whether individual-level associations between response bias *c* for Black targets and self-reported bias varied depending on regional bias, by including interaction terms between individual and regional predictors.

Table 5 and Figure 5 depict the results of these analyses. We observed significant cross-level interactions: individual-level links between response bias *c* for Black targets and threat perceptions from Black targets, stereotypes associating Black people with weapons, and preference of White over Black people were stronger in regions with higher corresponding bias. No cross-level interaction was found for Bayesian racism.

Figure 6

Cross-level interactions between individual and regional bias in predicting response bias c for Black targets. Individual-level correlations between the tendency to detect weapons among Black (vs. White) targets and threat perceptions, weapon stereotypes, and group preferences were amplified in regions with stronger corresponding intergroup bias. No significant cross-level interaction was observed for Bayesian racism.



Links between regional structural characteristics and shooter biases

We explored whether structural regional characteristics – including racial demographics, segregation, income inequality, gun laws, handgun sales, violent crime, police killings, and hate crimes – were linked to regional shooter biases.

We aggregated population demographics (i.e., percentage of White residents between years 2018-2022), racial segregation (i.e., Theil index; higher values indicate greater segregation), violent crime rates (i.e., total number of violent crimes reported per 100,000 people in 2020), income inequality (i.e., Gini Index between years 2018-2022), and disproportionate police killings (i.e., the difference between percentage of Blacks killed in each CBSA relative to the total number of individuals killed by police officers minus the percentage of Blacks living in each CBSA between the years 2013-2025, see Hehman et al., 2019) at the CBSA level. We retrieved these structural regional characteristics from https://policymap.com/ on Feb 20, 2024. Data on police killings were retrieved from https://mappingpoliceviolence.us/cities.

Several further structural characteristics were better operationalized – or, in some cases, only available – at the state level. Structural regional characteristics operationalized at the state level were gun law strength (as of January, 2023; retrieved from https://everytownresearch.org on Feb 20, 2024), handgun sales (retrieved from https://www.safehome.org/data/firearms-guns-statistics/ on Feb 20, 2024), and hate crimes (rate of hate crimes with an anti-race, anti-ethnicity, or anti-ancestry bias reported per 100,000 people in 2006-2018; retrieved from https://policymap.com/ on Feb 20, 2024).

Because participants were sampled by CBSA, state-level sample sizes varied (*n*s = 1–140). All else equal, estimates will be more precise in states with relatively more responses.To account for this variation, we used a multiverse approach, running models that excluded states with fewer than 5, 20, or 50 participants – resulting in 36, 34, and 16 states, respectively – to test the robustness of results against differences in measurement precision.

CBSA-level correlations are shown in Table 4; state-level results of multiverse analyses are in the Supplement (Figure S1). Shooter bias in reaction times was smaller in more segregated CBSAs (r = -.21) and larger in states with stricter gun laws (rs = .40 -.60). Segregated CBSAs also showed stronger weapon detection tendencies for both Black (r = -.23) and White (r = -.27) targets, and lower accuracy for detection weapons among Black targets (r = -.32). Higher income inequality was linked to lower accuracy for both Black (r = -.28) and White (r = -.21) targets. Lastly, participants were less likely to detect weapons among White targets in states with more hate crimes (rs = .34-.37).

Discussion

Leveraging data from 2,043 White participants across 100 U.S. regions, this study examined how individual and regional stereotypes and prejudice relate to shooter bias, offering new insights into the role of geographic context in biased decision-making.

At the individual level, we observed patterns consistent with prior research. Participants showed a robust shooter bias in reaction times (η_p^2 = .098), responding faster to armed Black than White targets and slower to unarmed Black than White targets. We observed no shooter bias in error rates and no response bias in signal detection analyses, consistent with prior findings that shooter bias typically appears in either latency or accuracy, but rarely in both (Correll et al., 2002; 2007). Response bias c for Black targets showed small but significant correlations with prejudice and stereotypes (|rs| = .05–.10), replicating effect sizes from a meta-analysis (Mekawi & Bresin, 2015). These effects were detectable given the study's high power ($1 - \beta$ = .99). Shooter bias in reaction times was unrelated to self-reported bias.

At the regional level, response bias *c* for Black targets was more strongly associated with prejudice and stereotypes than at the individual level ($|rs|$ = .22–.34). No such links were found for reaction times or error rates. These stronger regional correlations align with prior research (e.g., Hehman et al., 2019) and may reflect reduced measurement error (Connor & Evers, 2020), contextual influences (Payne et al., 2017), or both (Calanchini et al., 2022).

Taken together, across levels of analysis, the study linked shooter bias to stereotypes and prejudice, shedding light on psychological mechanisms behind biased decisions and supporting the task's validity as a bias measure. Notably, whereas the shooter task is typically understood as reflecting threat-related stereotypes, our findings align with a small but growing body of work suggesting that prejudice, too, may be relevant for biased decision-making in policing contexts (see Stelter et al., 2022).

This study advances regional bias research by using multilevel modeling to disentangle individual and regional links with shooter bias. It showed that regional bias uniquely contributes to shooter bias beyond individual stereotypes and prejudice. Moreover, the relationship between shooter bias and self-reported bias was stronger in high-bias regions. This may reflect weaker influences of anti-bias norms in high-bias regions, reducing social pressure to regulate biased behavior. Conversely, stronger anti-bias norms in low-bias regions may promote self-regulation, weakening the link between personal bias and shooter bias.

Furthermore, the regional approach allowed us to link shooter bias to macro-level variables beyond the traditional purview of shooter bias research. Participants in states with more race-related hate crimes were less inclined to detect weapons among White targets. Also, shooter bias in reaction times was smaller in racially segregated regions but larger in areas with stricter gun laws – contrasting with prior findings (Mekawi & Bresin, 2015). These differences may reflect shifts in public attitudes, broader geographic coverage, or improved statistical power from our larger, more recent sample.

What is the Most Appropriate Way to Operationalize Shooter Bias?

In our study, reaction time and error-based scores, which rely on double-difference calculations, showed near-zero internal consistency, limiting their ability to detect meaningful associations (Lord & Novick, 1968; Nunnally, 1970). In contrast, signal detection modeling separates sensitivity *d'* from response bias c, offering a more precise and reliable framework, parsing variance into distinct cognitive processes. Only *c* correlated with self-reported bias, likely due to its higher reliability ($|r\text{s}|$ = .32–.44) compared to reaction time and error-based scores ($|r\text{s}|$ = -.01–.17). These findings support response bias *c* as the preferred operationalization of shooter bias.

What is the Appropriate Unit of Analysis to Capture Regional Bias?

One goal of this research was to examine how shooter bias relates to regional characteristics, including structural indices and aggregated intergroup bias. Although individual biases are shaped by broader contexts (Payne et al., 2017), our findings revealed low between-region variance in prejudice and stereotypes, as indicated by low intraclass correlations (ICCs). This may be because Core-Based Statistical Areas (CBSAs), which can span multiple counties, are too large or heterogeneous to capture localized bias. Future research should consider more granular units to better detect local patterns. Despite low ICCs, regional correlations were stronger than individual correlations – likely due to the benefits of aggregation, which reduces noise and amplifies shared environmental influences. These findings underscore the importance of selecting appropriate geographic units, as finer-grained boundaries may yield more accurate insights into how social environments are linked to discriminatory behavior.

Limitations

This study has several limitations. First, we used a convenience sample of internet volunteers, limiting generalizability. Our focus was on relationships among bias measures rather than population estimates, but future research should replicate these findings with representative samples. Importantly, most regional bias research relies on Project Implicit data, which constrains external validity (Calanchini et al., 2022); by collecting new data, the present study contributes meaningfully to the generalizability of this growing literature. Second, our correlational design does not support causal claims, and reciprocal influences between individual and regional biases are possible. Third, we used manifest variables in multilevel models, which may conflate true contextual effects with reduced error from aggregation. Future work should consider latent modeling (Lüdtke et al., 2008). Finally, we restricted the sample to White participants to reduce heterogeneity, which enhances internal validity but limits generalization. Future studies should replicate and extend these findings in more racially diverse samples.

Conclusion

This study offers a multilevel perspective on shooter bias, integrating individual psychological factors with broader regional contexts. Regional bias predicted shooter bias directly and moderated individual-level effects, suggesting that discriminatory behavior is shaped by both personal beliefs and social environments. By introducing new data beyond commonly used sources, this research enhances the generalizability of regional bias findings. Future research should continue to refine measurement approaches, explore causal pathways, and examine how structural and normative factors influence discriminatory behavior.

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