Racial bias in police traffic stops: White residents' county-level prejudice and stereotypes
are related to disproportionate stopping of Black drivers

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Abstract

Racial disparities in policing are well documented, but the reasons for such disparities are often debated. The current research weighs in on this debate using a regional-level bias framework: We investigate the link between racial disparities in police traffic stops and regional-level racial bias, employing data from over 130 million police traffic stops in 1,413 US counties and county-level measures of racial bias from over 2 million online participants. Compared to county demographics, Black drivers were stopped at disproportionate rates in the majority of counties. Crucially, disproportionate stopping of Black drivers was higher in counties with higher levels of racial prejudice by White residents ($r_s = 0.07 - 0.36$). Furthermore, county-level aggregates of Whites' threat-related stereotypes were less consistent in predicting disproportionate stopping ($r_s = 0.00 - 0.19$). These observed relationships between regional-level bias and racial disparities in policing highlight the importance of context in which police operate.

Keywords: regional-level bias; police traffic stops; systemic bias; prejudice; stereotypes

Word count: 2,199

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Statement of Relevance

In the US, Black drivers are stopped with disproportionate frequency and these traffic stops are often starting points for multiple forms of racial disparities in policing. Current societal debates center on whether this is the result of widespread racial bias or should be attributed to the actions of a few rogue police officers. Analyzing massive datasets of more than 130 million traffic stops from 1,413 US-counties, our findings indicate that White residents' racial bias aggregated at the county-level relates to racial disparities in police traffic stops. These findings suggest that research on racial disparities in policing should not only focus on individual officers, but should also examine the social contexts in which police operate.

Introduction

Racial disparities in policing are well documented, ranging from higher rates of Black Americans being stopped, questioned or frisked (e.g., Eberhardt, 2016), to incidents of police brutality and shootings (e.g., Hester & Gray, 2018; Voigt et al., 2017), but there is an ongoing debate about the reasons for such disparities. Some argue that racial disparities in policing are rooted in widespread racial bias (e.g., Lowery, 2020), others argue that rather “a few bad apples” are responsible for police misconduct (e.g., Benner, 2020). Such disparate views indicate that merely documenting racial disparities in policing does neither offer sufficient explanation nor ways to overcome them (Hetey & Eberhardt, 2018). The present research contributes to this debate by investigating whether the contexts in which police officers operate relate to racial disparities in policing outcomes.

Our analyses focus on police traffic stops, which represent the most common situation in which Americans encounter police (Davis & Whyde, 2018). Broadly, two approaches

have investigated racial disparities in policing: field and lab studies. Field research demonstrates that Black drivers are stopped at higher rates than White drivers (e.g., Gelman, Fagan, & Kiss, 2007; Langton & Durose, 2013; Pierson et al., 2020; Warren, Tomaskovic-Devey, Smith, Zingraff, & Mason, 2006). Furthermore, traffic stops are often starting points for further racial disparities in policing: Once stopped, Black Americans are treated less respectfully (Voigt et al., 2017), are more likely searched (e.g., Higgins, Jennings, Jordan, & Gabbidon, 2011; Pierson et al., 2020), arrested (e.g., Kochel, Wilson, & Mastrofski, 2011), and exposed to more excessive use of force than White Americans (e.g., Edwards, Lee, & Esposito, 2019; Fryer, 2019). Thus, police traffic stops can set in motion a cascade of events that may threaten people's lives and livelihoods, ultimately undermining trust in law enforcement (Camp, Voigt, Jurafsky, & Eberhardt, 2021).

While such field studies document the extent of racial disparities, they often only allow indirect inferences of why these disparities occur. For example, Pierson and colleagues (2020) conducted a "veil-of-darkness test" to examine racial profiling in police traffic stops. The rationale behind this test is the following: If disproportionate stopping of Black drivers was indeed caused by biased decision making, racial disparities should be larger during daylight, when drivers' racial group membership is easier categorized, compared to during darkness (Grogger & Ridgeway, 2006). Consistent with this reasoning, Black drivers were indeed less likely to be stopped in darkness compared to daylight, suggesting that racial group membership might play a role in officers' stop decisions (but see Worden, McLean, & Wheeler, 2012). Yet, such indirect tests of racial bias in field research are limited in that they cannot investigate police officers' attitudes, motives, and behavioral decisions while on duty. Alternatively, lab studies allow more fine-grained analyses of psychological processes in police officer behavior. For example, some studies link racial disparities in use of force decisions to threat-related stereotypes (cf. Correll, Wittenbrink, Crawford, & Sadler, 2015) or prejudice (e.g., Eberhardt, Goff, Purdie, & Davies, 2004). This research provides insights into cognitive and affective processes in split-second decisions. However, it is

debatable to what extent findings in the lab generalize to real-world police encounters, with lab studies potentially underestimating (Jasperse, Stillerman, & Amodio, 2021) or overestimating (Cesario, 2021) effects of bias in real-world decision making. The current research combines both approaches to examine racial disparities in policing by connecting psychological studies of intergroup biases and field data of policing outcomes within a regional-level bias framework (e.g., Hehman, Calanchini, Flake, & Leitner, 2019).

Applying this approach, a growing number of studies have aggregated measures of prejudice and stereotypes at the regional level (e.g., counties; states) to investigate relationships between racial bias and racial disparities in societal outcomes. Such studies have demonstrated that racial disparities in policing, healthcare, and education are more likely in regions where residents demonstrate higher levels of racial bias than in regions with lower levels of racial bias (e.g., Hehman, Flake, & Calanchini, 2018; Orchard & Price, 2017; Riddle & Sinclair, 2019). Recently, Payne, Vuletich, and Lundberg (2017) proposed a theoretical framework for such findings, conceptualizing racial stereotypes and prejudice as relatively stable characteristics of contexts (rather than people), making the activation of biased thoughts and feelings in some contexts more likely than in others. Building on this idea, racial disparities in policing may thus not (entirely) depend on individual attitudes of police officers but also on the contexts in which they act. There is evidence that policing outcomes vary by region (e.g., <https://policescorecard.org>) and these differences may relate to characteristics of the local environment that affect both local residents' racial biases and policing behavior. For example, region-specific crime levels, racial segregation, and quality and quantity of intergroup contact, as well as local politics, or media content may affect whether and how strongly Black people are linked to stereotypes of criminality and threat (e.g., Sim, Correll, & Sadler, 2013). Consequently, in regions with higher levels of crime- or threat-related stereotyping, police officers might be cued to interpret Black drivers' behavior as suspicious. Another possibility is that regional levels of anti-Black and/or pro-White prejudice might affect racial disparities in police traffic stops. Higher regional

levels of hostility toward Black people might increase police officers' inclination to stop Black drivers as a means of nuisance or harassment. Alternatively, higher regional levels of liking of White people might increase police officers' inclination to spare White drivers the nuisance of a traffic stop. Importantly, given that stereotypes and prejudice can be both related or distinct components of intergroup attitudes (e.g., Amodio & Devine, 2006; Phills, Hahn, & Gawronski, 2020), regional-level stereotypes and prejudice may independently or interactively relate to racial disparities in police traffic stops.

Based on these considerations, the present research investigates both, regional levels of racial stereotypes and prejudice and their relationships with racial disparities in police traffic stops using large, publicly accessible datasets. We link county-level aggregates of several measures of racial stereotypes and prejudice to county levels of racial disparities in police traffic stops. Societal racial bias and discrimination is described as relying on White power structures (e.g., Berard, 2008), and classic intergroup theories in social psychology suggest that societal institutions (e.g., law enforcement) are largely shaped by dominant groups (e.g., Sidanius & Pratto, 1999). Consequently, we focus our analyses on White residents' aggregates of stereotyping and prejudice as proxies of regional-level bias.¹

Methods

Data sources

Police traffic stops. We retrieved data on police traffic stops from the Stanford Open Policing Project (Pierson et al., 2020), which collects and standardizes data on vehicle and pedestrian stops from law enforcement departments across the United States. Our analyses include data on 134,016,874 state patrol traffic stops located in 1,413 counties across 24 US states documented between the years 2000 and 2018. We included all traffic

¹ We report additional analyses with Black residents' racial bias in the Supplement (Table S10 and Figure S3). These analyses show no consistent relationships between Black residents' racial bias and racial disparities in police traffic stops.

stops for which drivers' race and county information was reported. For three states (IL, NJ, and VT), we derived county information based on zip codes and/or municipalities. We analyzed vehicle stops only and excluded data on pedestrian stops. For each county, we calculated the percentage of Black drivers among all stopped drivers. To examine whether Black drivers were stopped at disproportionate rates relative to their population share at the county level, we subtracted the percentage of Black residents in each county (as reported by the 2017 Census, U.S. Census Bureau, 2017) from the percentage of Black drivers stopped in each county. This resulted in a score of disproportionate stopping of Black drivers with zero indicating no disproportion and a positive score indicating stopping rates higher than expected based on county population.

Racial Stereotypes and Prejudice. Measures of racial stereotypes and prejudice were retrieved from Project Implicit (Xu et al., 2017). Threat-related stereotypes were measured with two items asking participants how much they associate Black people relative to White people with weapons and harmless objects, and a Weapons IAT. Prejudice was measured with feeling thermometers, an item asking respondents for their relative preference for White people relative to Black people, and an evaluative Race IAT. We included data collected between 2002 and 2018 from US American respondents who self-identified as White and for whom geographic information was reported. Based on respondents' geographic information, we aggregated measures of prejudice and stereotypes at the county-level.

Weapons IAT. In the Weapons IAT, participants use two response keys to classify Black and White faces according to race and images of weapons or harmless objects. Faster responses and fewer errors in trials during which White faces and harmless objects share one response key and Black faces and weapons share another response key (versus the reverse pairing) are interpreted as an indirect indication of threat-related stereotype representations of Black people relative to White people. Responses were converted into IAT *D* scores (Greenwald, Nosek, & Banaji, 2003). Higher IAT *D* scores indicate a stronger

stereotype effect.

Self-reported racial stereotypes. As measures of self-reported endorsement of threat-related racial stereotypes, we analyzed participants' ratings on two items assessing how much they associate weapons and harmless objects with Black and White people on scales ranging from 1 (*Strongly with White people/White Americans*) to 7 (*Strongly with Black people/Black Americans*). We converted scales to range from -3 to $+3$.

Evaluative Race IAT. In the Race IAT, participants use two response keys to classify Black and White faces according to race and positive and negative words (e.g., lovely, terrible) according to valence. Faster responses and fewer errors in trials during which White faces and positive words share one response key and Black faces and negative words share another response key (versus the reverse pairing) are interpreted as an indirect indication of pro-White/anti-Black evaluations (i.e., racial prejudice). Higher IAT D scores in the Race IAT indicate a stronger preference for White relative to Black people.

Self-reported racial prejudice.

Preference for Whites. As a measure of self-reported racial prejudice, we analyzed respondents' relative preference for White people relative to Black people on a scale ranging from "*I strongly prefer African Americans to European Americans*" to "*I strongly prefer European Americans to African Americans.*" Number of scale points vary between different versions of the item (5-point scale used between 2004 and 2006; 7-point scale used between 2006 and 2017). We converted values from both versions to a combined scale ranging from -3 to $+3$.

Feeling thermometer bias. As a second measure of self-reported racial prejudice, we analyzed respondents' felt warmth towards White people and Black people on scales ranging from 0 (*very cold*) to 10 (*very warm*). We converted values to range from 0 to $+3$ and computed a difference score (ranging from -3 to $+3$) such that positive values indicate relatively higher warmth felt for Whites compared to Blacks.

Analysis Plan

To increase reliability for measures of stereotypes and prejudice, previous research has applied selection criteria of minimum respondents per county to be included in analyses [e.g., restricting analyses to 100 or 150 respondents per geographical unit; Hehman, Flake, and Calanchini (2018); Payne, Vuletich, and Brown-Iannuzzi (2019)]. Applying such fixed selection criteria is often arbitrary and without theoretical justification. Also, restricting the number of respondents reduces the number of counties included in analyses, and may thereby reduce test power. To circumvent these problems and to increase transparency, we employed a multiverse approach, reporting findings across different selection criteria (i.e., including counties with more than 0, 25, 50, 75, 100, and 150 respondents, respectively).

We first computed zero-order correlations between disproportionate stopping of Black drivers and county-level stereotype and prejudice aggregates. To further examine the incremental value of different prejudice and stereotype measures and to control for potential covariates, we then tested several multiple regression models. In a first series of models, we compared the contributions of different stereotype measures in predicting disproportionate stopping of Black drivers. Similarly, in a second series of models, we compared the contributions of different prejudice measures in predicting disproportionate stopping. In a third series of models, we compared the contributions of prejudice and stereotypes in predicting disproportionate stopping by adding all stereotype and prejudice measures as predictors. In a fourth and fifth series of models, we controlled for potential effects of county demographics, adding the percentage of Black and White residents as further predictors into the models. In a final set of analyses, we performed a veil-of-darkness test (Grogger & Ridgeway, 2006) and analyzed separate correlations between measures of racial bias and disproportionate stopping of Black drivers during daylight and darkness.

All analyses were conducted in R [Version 4.1.0; R Core Team (2019)] and the R-packages *broom.mixed* [Version 0.2.7; Bolker and Robinson (2021)], *corx* [Version 1.0.6.1;

Conigrave (2020)], *cowplot* [Version 1.1.1; Wilke (2019)], *data.table* [Version 1.14.0; Dowle and Srinivasan (2019)], *gridExtra* [Version 2.3; Auguie (2017)], *here* [Version 1.0.1; Müller (2017)], *jtools* [Version 2.1.3; Long (2020)], *knitr* [Version 1.33; Xie (2015)], *lattice* [Version 0.20.44; Sarkar (2008)], *lme4* [Version 1.1.27.1; Bates, Mächler, Bolker, and Walker (2015)], *lmerTest* [Version 3.1.3; Kuznetsova, Brockhoff, and Christensen (2017)], *lsr* [Version 0.5; Navarro (2015)], *MBESS* [Version 4.8.0; Kelley (2019)], *MuMIn* [Version 1.43.17; Bartoń (2020)], *papaja* [Version 0.1.0.9997; Aust and Barth (2020)], *tidyverse* [Version 1.3.1; Wickham (2017)], and *usmap* [Version 0.5.2; Di Lorenzo (2021)]. Our analysis codes are publicly accessible via the Open Science Framework (reviewer link: https://osf.io/3cjk9/?view_only=da305c3223b3420eb28d94fa2265c7b6).

Results

Preliminary analyses

Police traffic stops. Compared to their share in the county populations, Black drivers were stopped 2.75 % ($SD = 5.38$) more often. This score is significantly greater than zero, as tested by a two-sided one-sample t-test, $t(1412) = 19.25$, $p < .001$, $d = 0.51$, 95% CI [0.46; 0.57], indicating disproportionate stopping of Black drivers. Percentiles of county-level disproportionate stopping of Black drivers are illustrated in Figure 1, Panel A.

Racial stereotypes and prejudice. Table 1 reports a descriptive summary of stereotype and prejudice measures for different selection criteria, and restricted to counties for which we obtained data on police traffic stops. Results from the Weapons IAT and from self-reported stereotypes showed that, on average, White residents associate Black people with weapons, whereas they associate White people with harmless objects. Furthermore, White residents' Race IAT D scores indicate an overall preference for Whites relative to Blacks. Similarly, White residents' self-reported measures of prejudice indicate an overall preference for Whites and higher perceptions of warmth toward Whites

compared to Blacks. Self-reported measures of prejudice were highly correlated at the county-level ($rs = 0.71-0.85$). We therefore converted both measures into z-scores and averaged them to a combined score of self-reported racial prejudice for the regression analyses. Figure 1 (Panel B and C) illustrates percentiles of White residents' county-level Race IAT D scores and the combined score for self-reported racial prejudice.

Correlational analyses.

Zero-order correlations. Figure 2 illustrates correlations between disproportionate stopping of Black drivers and county levels of White residents' Weapon IAT D scores, self-reported racial stereotypes, Race IAT D scores, and self-reported preference and felt warmth for Whites relative to Blacks (see also Table S2).

There were no correlations between White residents' Weapon IAT D scores and disproportionate stopping of Black drivers ($rs = 0.00 - 0.03$). However, we observed consistently positive correlations between self-reported associations of Blacks with weapons and disproportionate stopping of Black drivers, regardless of selection criteria ($rs = 0.11 - 0.19$). Furthermore, we observed negative correlations between disproportionate stopping of Black drivers and self-reported associations of Blacks with harmless objects, but only when including counties with a minimum of 100 or 150 respondents ($rs = -0.08 - 0.03$). Finally, we observed positive correlations between disproportionate stopping of Black drivers and Race IAT D scores ($rs = 0.07 - 0.30$), self-reported preference for Whites ($rs = 0.17 - 0.36$), and felt warmth for Whites ($rs = 0.13 - 0.31$), regardless of selection criteria. Overall, results indicate that disproportionate stopping of Black drivers was more prevalent in counties with higher levels of racial bias on four out of six measures and across different selection criteria.

Table 1
County-level descriptive statistics of White residents' racial stereotype and prejudice measures

Exclusion criteria	Weapons IAT		Stereotype Harmless		Stereotype Weapons		Race IAT		Preference Score		Feeling Thermometer	
	M (SD)	N	M (SD)	N	M (SD)	N	M (SD)	N	M (SD)	N	M (SD)	N
All counties	0.35 (0.15)	1,413	-0.15 (0.27)	3,050	0.16 (0.42)	3,050	0.39 (0.09)	1,413	0.53 (0.22)	3,126	0.23 (0.14)	3,126
> 25 respondents	0.36 (0.05)	749	-0.16 (0.10)	1,410	0.20 (0.18)	1,413	0.39 (0.05)	1,108	0.53 (0.14)	2,398	0.23 (0.08)	2,429
> 50 respondents	0.36 (0.04)	585	-0.16 (0.08)	995	0.21 (0.16)	1,002	0.39 (0.04)	915	0.52 (0.12)	1,930	0.23 (0.07)	1,960
> 75 respondents	0.36 (0.04)	491	-0.16 (0.07)	800	0.22 (0.15)	803	0.39 (0.04)	806	0.52 (0.12)	1,653	0.23 (0.07)	1,683
> 100 respondents	0.36 (0.03)	438	-0.16 (0.06)	673	0.22 (0.14)	676	0.39 (0.04)	740	0.52 (0.11)	1,484	0.23 (0.07)	1,504
> 150 respondents	0.36 (0.03)	368	-0.16 (0.06)	530	0.23 (0.14)	533	0.39 (0.04)	635	0.52 (0.11)	1,234	0.23 (0.07)	1,264

Note. Weapons IAT = Weapons IAT D score; Stereotype Harmless = self-reported rating of how much harmless objects are associated with Black and White people; Stereotype Weapons = self-reported rating of how much weapons are associated with Black and White people; Race IAT = Evaluative Race IAT D score; Preference Score = preference for Whites relative to Blacks on one-item preference measure; Feeling Thermometer = feeling thermometer difference score for Whites relative to Blacks; positive scores on racial prejudice and stereotype measures indicate less favorable evaluations and more negative stereotypes of Blacks relative to Whites, whereas negative scores on racial prejudice and stereotype measures indicate more favorable evaluations and less negative stereotypes of Blacks relative to Whites. N represents number of counties.

A

B

C

Figure 1. Map of US counties indicating percentiles of county-level disproportionate stopping of Black drivers (Panel A), county-level Race IAT D scores (Panel B), and county-level self-reported racial prejudice (Panel C).

Figure 2. Zero-order correlations between county-level disproportionate stopping of Black drivers and county-level measures of White residents racial stereotypes and prejudice.

Figure 3. Regression Models. Predictors of disproportionate stopping of Black drivers are depicted on the y-axis. Data-points represent standardized regression coefficients. Error bars represent 95% confidence intervals.

Multiple regression models. In order to test unique contributions of different measures of racial stereotypes and prejudice in predicting disproportionate stopping of Black drivers, we conducted several regression analyses (see Figure 3 and Tables S3 to S8 in the Supplement). To account for the hierarchical data structure with counties nested within states, we fitted linear mixed-effects models. In a first model, we included stereotype measures (i.e., Weapons IAT D scores and self-reported racial stereotypes) as predictors. In this model, none of the predictors were consistently related to disproportionate stopping of Black drivers (conditional $R_s = 0.20 - 0.40$; marginal $R_s = 0.00 - 0.01$). In a second model, we included prejudice measures (i.e., Race IAT D scores

and self-reported racial prejudice as the combined score of preference for Whites and feeling thermometer bias) into the model. In this model, only self-reported racial prejudice was a consistent significant predictor of disproportionate stopping of Black drivers (conditional $Rs = 0.18 - 0.35$; marginal $Rs = 0.01 - 0.05$). In a third model, we included all stereotype and prejudice measures into the model. In this model, again only self-reported racial prejudice was a consistent significant predictor of disproportionate stopping of Black drivers (conditional $Rs = 0.19 - 0.33$; marginal $Rs = 0.02 - 0.06$).

Previous research suggests that racial bias is related to regional demographics, such as the percentage of Black or White people living in a region (e.g., Rae, Newheiser, & Olson, 2015). Consequently, we conducted analyses, adding county proportions of Black and White residents as control variables. Because these variables were highly correlated ($r = -0.91$), we fitted two separate models, adding county proportions of Black residents in a fourth model (conditional $Rs = 0.51 - 0.59$; marginal $Rs = 0.08 - 0.21$) and White residents in a fifth model (conditional $Rs = 0.43 - 0.46$; marginal $Rs = 0.07 - 0.14$). These models indicated that county demographics were significant predictors, with lower proportions of Black residents and higher proportions of White residents being related to higher disproportionate stopping of Black drivers. Importantly, self-reported racial prejudice remained a significant independent predictor of disproportionate stopping of Black drivers in both models.

Veil-of-Darkness Test. To perform a so-called veil-of-darkness test, we followed recommendations from previous research (e.g., Grogger & Ridgeway, 2006; Pierson et al., 2020; Worden, McLean, & Wheeler, 2012), restricting data for police stops to those times of the day that can be either light or dark, depending on seasonal shifts of sunset. By restricting the data to this inter-twilight period, we can rule out that effects are potentially confounded by differences in driving patterns (i.e., one group driving more often during earlier or later hours of the day). In addition, we removed stops during the ambiguous twilight period of approximately 30 minutes between sunset and dusk. Note that these

restrictions considerably reduce the number of police stops included in our analyses to 9,506,820 stops during daylight and 9,140,738 stops during darkness, measured in 1,022 counties in 15 states. Our analyses demonstrate that proportions of stopped Black drivers in comparison to Black county population were lower during daylight ($M = 2.23$, $SD = 5.21$) than during darkness ($M = 2.44$, $SD = 4.56$, $t(1,009) = -5.21$, $p < .001$), $dz = -0.16$, 95% $CI [-0.23; -0.10]$. Thus, different to Pierson et al. (2020), our analyses did not reveal greater disparities at daylight (during which drivers' race is presumed to be more visible). Note that our analyses differed from the analyses reported by Pierson et al. in two ways: First, our analyses are less restrictive in terms of data inclusion, as Pierson et al. further restricted their analyses to data from the 60-day windows before and after the beginning of daylight saving time. Second, different from Pierson et al., our analyses were based on county-aggregates, relating proportions of stopped Black drivers to proportions of Black county populations. These differences in analysis strategies may account for the different results. Applying the same correlational analyses as above to police stops at daylight versus darkness, results showed that relationships between racial bias and disproportionate stopping of Black drivers are almost identical for both lighting conditions (see Figure 4).

Figure 4. Zero-order correlations between county-level disproportionate stopping of Black drivers and county-level measures of White residents' racial stereotypes and prejudice during daylight (upper panel) and during darkness (lower panel).

General Discussion

Combining data of over 130 million traffic stops with regional aggregates of racial prejudice and stereotypes, we observed that racial disparities in police traffic stops were related to Whites' local levels of racial bias. These relationships were observed across different model specifications, highlighting their robustness. Relationships between racial bias and police traffic stops were consistent across different measures of racial prejudice,

but less consistent across measures of threat-related racial stereotypes. Furthermore, these relationships were observed regardless of daytime and after controlling for county demographics. The present findings are consistent with previous field studies documenting racial disparities in policing (e.g., Pierson et al., 2020). Connecting policing data to psychological studies of intergroup biases, our approach adds another layer by demonstrating robust relationships between racial disparities in policing outcomes and the contexts in which police officers operate.

Our finding that White county residents' racial bias was associated with county-level racial disparities in traffic stops is consistent with other findings, such as that Black people were disproportionately shot by police in regions with higher levels of racial prejudice and threat-related stereotypes (Hehman, Flake, & Calanchini, 2018). While overall consistent, present results depart from this prior finding in two ways. First, we observed stronger relationships for self-report measures than for indirect measures of racial bias. Second, our findings suggest that in stop decisions, prejudice toward Black people might be more relevant than threat-related racial stereotypes. These discrepancies might be explained by situational differences between shoot versus stop decisions: Shoot decisions may occur more often in situations involving perceived immediate threats of physical harm, eliciting high arousal and fear, and potentially reducing deliberate behaviors while increasing influences of threat-related stereotypes on police officers' behavior (e.g., Correll, Hudson, Guillermo, & Ma, 2014). Consequently, situations surrounding shoot decisions should relate more closely to measures of threat-related stereotypes (cf. March, Olson, & Gaertner, 2020). Conversely, relationships between stop decisions and measures of threat seem less clear.

The role of prejudice in stop decisions is worth highlighting. Some scholars have argued that disparities in policing do not necessarily reflect racial bias, but instead reflect that Black people are more often involved in crime, which in turn shapes people's racial stereotypes (e.g., Cesario, 2021). The present findings challenge such notions, suggesting that relative liking and preference for White people over Black people played a more

important role in racial disparities in police traffic stops than stereotypes (cf. Essien, Stelter, Rohmann, & Degner, 2021).

The observed relationships between regional-level bias and police traffic stops underscore the role of context in which police officers operate. Our findings are consistent with theorizing by Payne, Vuletich, and Lundberg (2017), who argued that some contexts expose individuals more regularly to stereotypes and/or prejudice, increasing mental accessibility of biased thoughts and feelings, in turn influencing individual behavior. Consequently, behavioral expressions of prejudice and stereotypes often reflect properties of contexts rather than stable dispositions of people (but see Connor & Evers, 2020).

One possible explanation of how regional-level bias might affect policing is that it reflects regional norms that interact with institutionalized practices in law enforcement. For example, police traffic stops in the US are regularly used as investigative tools that encourage officers to maximize the number of traffic stops based on “suspicion of criminal activity” (Epp, Maynard-Moody, & Haider-Markel, 2017, p. 172). Although racially neutral on the surface, such practices may connect regional-level bias with police officers’ behavior: Incentives to maximize the number of stops in conjunction with local norms that favor Whites might encourage police officers to disproportionately stop Black drivers. Moreover, when instructed to base initial stop decisions on “gut feelings,” officers may rely on contextually available prejudice or stereotypes (De Houwer & Tucker Smith, 2013; Epp, Maynard-Moody, & Haider-Markel, 2017; Swencionis, Pouget, & Goff, 2021). Additionally, racial bias of supervisors may affect decisions to direct officers to regions where they more likely encounter Black drivers (cf. Beckett, Nyrop, & Pfingst, 2006), consistent with documentations of over-patrolling of minority areas (Vomfell & Stewart, 2021). Thus, racial bias may affect investigatory stops even in the absence of prejudice or stereotyping on part of the individual police officers involved. Future research needs to identify the psychological mechanisms that mediate between community racial bias and officer behavior, for example by including direct investigation of institutionalized practices in law enforcement.

The veil-of-darkness test did not demonstrate greater racial disparities in police traffic stops during daylight compared to darkness, thus departing from previous research relying on similar data (Pierson et al., 2020). While intuitively convincing, darkness may not necessarily eliminate social categorization of drivers (e.g., due to artificial lighting), especially because racial categorization has been shown to be robust to sub-optimal viewing conditions (e.g., Kawakami, Amodio, & Hugenberg, 2017). Given that the validity of the veil-of-darkness test hinges on a number of assumptions (e.g., that police officers use person features rather than other information, such as vehicle type), and given other studies, which did not observe relationships between lighting conditions and racial disparities in police traffic stops (e.g., Worden, McLean, & Wheeler, 2012), future research is needed to understand the boundary conditions of the veil-of-darkness test. Importantly, correlations between racial bias measures and disproportionate stopping rates were unaffected by lighting conditions, underlining the robustness of these relationships.

The present research has limitations. First, the correlational approach does not allow causal interpretations. Based on previous theorizing (Payne, Vuletich, & Brown-Iannuzzi, 2019), we suggest that regional-level bias provides a context that potentially affects police officer behavior. Alternatively, racial disparities in police traffic stops might affect regional-level bias by triggering negative evaluations linking Blacks with crime (e.g., Hetey & Eberhardt, 2018). It is also possible that a third variable affects both, racial bias and policing behavior. For example, regional differences in socioeconomic disparities between Black and White residents might affect both, racial bias and policing. This non-exhaustive list of alternative causal relationships illustrates the need for future research. Another limitation originates from the use of Project Implicit data (Xu et al., 2017), which are not representative of the US population. Participants visit the demonstration website voluntarily and skew liberal (e.g., Essien, Calanchini, & Degner, 2020). Similarly, based on available data sets, our analyses included only one-third of US counties, excluding data for many Midwestern and Southern states. Consequently, we do not know whether or how

including these regions might alter conclusions of this research.

Despite these limitations, it is important to highlight that the observed relationships were consistent across different measures of racial bias and relied on millions of online participants and tens of millions of traffic stops. Our findings suggest that analyses of racial disparities in policing should not only focus on individual officers, but also consider the contexts in which police operate.

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Supplementary material

Figure S1. Zero-order correlations of county-level disproportionate stopping of Black drivers with county-level Weapons IAT D scores, self-reported racial stereotypes (associations of weapons and harmless objects with Black people and White people), Race IAT D scores and self-reported measures of prejudice (preference for Whites and feeling thermometer bias).

Table S1

Descriptive statistics of White resident's racial stereotype and prejudice measures

	Exclusion criteria	M	SD	N (counties)	t	p	d	95% CI	N (respondents)
Weapons IAT	All counties	0.36	0.15	3,128	130.54	< .001	2.38	[2.31, 2.45]	449,434
	> 25 respondents	0.36	0.05	1,440	259.54	< .001	6.84	[6.58, 7.09]	434,998
	> 50 respondents	0.36	0.04	1,025	282.76	< .001	8.83	[8.44, 9.22]	419,807
	> 75 respondents	0.36	0.04	823	290.64	< .001	10.13	[9.63, 10.62]	407,264
	> 100 respondents	0.36	0.03	691	295.24	< .001	11.23	[10.63, 11.82]	395,776
	> 150 respondents	0.36	0.03	544	280.47	< .001	12.03	[11.30, 12.74]	377,495
Stereotype Harmless	All counties	-0.15	0.27	3,050	-30.75	< .001	-0.56	[-0.60, -0.52]	426,483
	> 25 respondents	-0.16	0.10	1,410	-58.54	< .001	-1.56	[-1.64, -1.48]	412,035
	> 50 respondents	-0.16	0.08	995	-63.93	< .001	-2.03	[-2.13, -1.92]	396,884
	> 75 respondents	-0.16	0.07	800	-64.46	< .001	-2.28	[-2.41, -2.15]	384,789
	> 100 respondents	-0.16	0.06	673	-65.20	< .001	-2.51	[-2.67, -2.36]	373,794
	> 150 respondents	-0.16	0.06	530	-61.76	< .001	-2.68	[-2.86, -2.50]	356,179
Stereotype Weapons	All counties	0.16	0.42	3,050	20.64	< .001	0.38	[0.34, 0.41]	429,216
	> 25 respondents	0.20	0.18	1,413	42.05	< .001	1.12	[1.05, 1.18]	414,736
	> 50 respondents	0.21	0.16	1,002	42.70	< .001	1.35	[1.26, 1.43]	399,732
	> 75 respondents	0.22	0.15	803	41.94	< .001	1.48	[1.38, 1.58]	387,417
	> 100 respondents	0.22	0.14	676	39.77	< .001	1.53	[1.42, 1.64]	376,413
	> 150 respondents	0.23	0.14	533	36.16	< .001	1.57	[1.44, 1.69]	358,825
Race IAT	All counties	0.39	0.09	3,128	249.83	< .001	4.47	[4.36, 4.59]	2,384,248
	> 25 respondents	0.39	0.05	2,472	381.24	< .001	7.67	[7.45, 7.88]	2,376,058
	> 50 respondents	0.39	0.04	2,013	397.16	< .001	8.85	[8.57, 9.13]	2,359,261
	> 75 respondents	0.39	0.04	1,729	406.96	< .001	9.79	[9.46, 10.12]	2,341,778
	> 100 respondents	0.39	0.04	1,549	406.69	< .001	10.33	[9.96, 10.70]	2,326,208
	> 150 respondents	0.39	0.03	1,288	400.52	< .001	11.16	[10.72, 11.59]	2,293,964
Preference for Whites	All counties	0.53	0.22	3,126	132.77	< .001	2.38	[2.31, 2.44]	2,164,333
	> 25 respondents	0.53	0.14	2,398	182.95	< .001	3.74	[3.62, 3.85]	2,155,219
	> 50 respondents	0.52	0.12	1,930	188.51	< .001	4.29	[4.15, 4.43]	2,138,033
	> 75 respondents	0.52	0.12	1,653	183.65	< .001	4.52	[4.36, 4.68]	2,120,850
	> 100 respondents	0.52	0.11	1,484	180.90	< .001	4.70	[4.52, 4.87]	2,106,115
	> 150 respondents	0.52	0.11	1,234	169.46	< .001	4.82	[4.62, 5.02]	2,075,547
Feeling Thermometer	All counties	0.23	0.14	3,126	94.95	< .001	1.70	[1.64, 1.75]	2,240,762
	> 25 respondents	0.23	0.08	2,429	139.80	< .001	2.84	[2.75, 2.93]	2,232,018
	> 50 respondents	0.23	0.07	1,960	140.79	< .001	3.18	[3.07, 3.29]	2,214,801
	> 75 respondents	0.23	0.07	1,683	136.39	< .001	3.32	[3.20, 3.45]	2,197,642
	> 100 respondents	0.23	0.07	1,504	132.11	< .001	3.41	[3.27, 3.54]	2,181,979
	> 150 respondents	0.23	0.07	1,264	123.39	< .001	3.47	[3.32, 3.62]	2,152,606
	All counties	0.36	0.15	3,128	130.54	< .001	2.38	[2.31, 2.45]	449,434

Note. Weapons IAT = Weapons IAT D score; Stereotype Harmless = self-reported rating of how much harmless objects are associated with Black and White people; Stereotype Weapons = self-reported rating of how much weapons are associated with Black and White people; Race IAT = Evaluative Race IAT D score; Preference for Whites = preference for Whites relative to Blacks on one-item preference measure; Feeling Thermometer = feeling thermometer difference score for Whites relative to Blacks; positive scores on racial prejudice and stereotype measures indicate less favorable evaluations and more negative stereotypes of Blacks relative to Whites, whereas negative scores on racial prejudice and stereotype measures indicate more favorable evaluations and less negative stereotypes of Blacks relative to Whites. All measures were tested with two-sided one-sample t-tests against zero.

Table S2

Zero-order correlations between White residents' racial stereotypes and prejudice and disproportionate stopping of Black drivers

		1	2	3	4	5	6	7
1. Disproportionate Stops	All counties	-	1330	1338	1338	1400	1401	1401
	Counties with > 25 respondents	-	682	676	676	1106	1071	1087
	Counties with > 50 respondents	-	515	504	506	908	872	886
	Counties with > 75 respondents	-	422	412	414	795	766	773
	Counties with > 100 respondents	-	368	358	359	731	706	713
	Counties with > 150 respondents	-	368	358	359	731	706	713
2. Weapons IAT	All counties	.00	-	1330	1330	1328	1328	1328
	Counties with > 25 respondents	.00	-	676	676	682	682	682
	Counties with > 50 respondents	.00	-	504	506	515	515	515
	Counties with > 75 respondents	.00	-	412	414	422	422	422
	Counties with > 100 respondents	.02	-	358	359	368	368	368
	Counties with > 150 respondents	.03	-	288	289	296	296	296
3. Stereotype Harmless	All counties	.03	-.07*	-	1338	1336	1336	1336
	Counties with > 25 respondents	.00	-.11**	-	676	676	676	676
	Counties with > 50 respondents	-.02	-.17***	-	504	504	504	504
	Counties with > 75 respondents	.01	-.20***	-	412	412	412	412
	Counties with > 100 respondents	-.08	-.29***	-	358	358	358	358
	Counties with > 150 respondents	-.07	-.26***	-	288	288	288	288
4. Stereotype Weapons	All counties	.11***	.11***	-.11***	-	1336	1336	1336
	Counties with > 25 respondents	.15***	.30***	-.28***	-	676	676	676
	Counties with > 50 respondents	.16***	.36***	-.36***	-	506	506	506
	Counties with > 75 respondents	.18***	.46***	-.37***	-	414	414	414
	Counties with > 100 respondents	.19***	.51***	-.41***	-	359	359	359
	Counties with > 150 respondents	.19***	.54***	-.43***	-	289	289	289
5. Race IAT	All counties	.07***	-.01	-.01	.21***	-	1400	1400
	Counties with > 25 respondents	.10***	.20***	-.06	.42***	-	1071	1087
	Counties with > 50 respondents	.20***	.27***	-.14**	.52***	-	872	886
	Counties with > 75 respondents	.24***	.32***	-.15**	.55***	-	766	773
	Counties with > 100 respondents	.27***	.37***	-.24***	.59***	-	706	713
	Counties with > 150 respondents	.30***	.43***	-.30***	.63***	-	598	613
6. Preference for Whites	All counties	.17***	-.01	-.07*	.09***	.26***	-	1401
	Counties with > 25 respondents	.25***	.09*	-.14***	.38***	.41***	-	1071
	Counties with > 50 respondents	.28***	.12**	-.16***	.44***	.56***	-	872
	Counties with > 75 respondents	.32***	.16**	-.19***	.46***	.59***	-	766
	Counties with > 100 respondents	.32***	.22***	-.31***	.50***	.61***	-	706
	Counties with > 150 respondents	.36***	.26***	-.38***	.54***	.66***	-	598
7. Feeling Thermometer	All counties	.13***	.00	-.12***	.10***	.25***	.71***	-
	Counties with > 25 respondents	.22***	.13***	-.24***	.50***	.43***	.77***	-
	Counties with > 50 respondents	.25***	.22***	-.30***	.55***	.54***	.80***	-
	Counties with > 75 respondents	.27***	.21***	-.35***	.58***	.58***	.83***	-
	Counties with > 100 respondents	.28***	.28***	-.45***	.59***	.61***	.84***	-
	Counties with > 150 respondents	.31***	.31***	-.52***	.63***	.65***	.85***	-

Note. * $p < .05$; ** $p < .01$; *** $p < .001$; values in the lower triangle represent correlation coefficients; values in the upper triangle represent number of pair-wise cases (i.e., number of counties).

Table S3

Inclusion of all counties: Racial disparities in police traffic stops predicted by racial stereotypes (Model 1), racial prejudice (Model 2), racial stereotypes and prejudice together (Model 3), as well as racial stereotypes and prejudice, controlling for county demographics (Models 4 and 5).

Predictor	Model 1			Model 2			Model 3			Model 4			Model 5		
	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t
Intercept	2.74	[1.54, 3.94]	4.47	< .001	2.22	[0.74, 3.70]	2.94	.004	1.87	[0.03, 3.70]	1.99	.047	3.26	[1.03, 5.49]	2.87
Weapons IAT	-0.10	[-1.79, 1.59]	-0.12	.906					-0.05	[-1.75, 1.64]	-0.06	.950	-0.68	[-2.19, 0.83]	-0.88
S Harmless	0.53	[-0.44, 1.50]	1.07	.285					0.75	[-0.23, 1.72]	1.50	.133	0.52	[-0.34, 1.39]	1.18
S Weapons	1.04	[0.40, 1.69]	3.17	.002					1.00	[0.34, 1.66]	2.98	.003	0.84	[0.25, 1.43]	2.80
Race IAT					-1.61	[-4.51, 1.28]	-1.09	.274	-0.96	[-4.54, 2.62]	-0.53	.600	0.10	[-3.10, 3.30]	0.06
Self-rep. prejudice					3.14	[1.61, 4.68]	4.02	< .001	3.57	[1.85, 5.30]	4.06	< .001	4.48	[2.93, 6.03]	5.68
% Black population													-0.22	[-0.24, -0.19]	-18.09
% White population															

Note: Weapons IAT = Weapons IAT D score; S Harmless Objects = self-reported rating of how much harmless objects are associated with Black and White people; S Weapons = self-reported rating of how much weapons are associated with Black and White people; Race IAT = Evaluative Race IAT D score; Self-rep. prejudice = combined score of measures of self-reported prejudice (i.e., preference for Whites and feeling thermometer difference score). For these models, number of respondents per county is not restricted.

Table S4

Counties with more than 25 respondents: Racial disparities in police traffic stops predicted by racial stereotypes (Model 1), racial prejudice (Model 2), racial stereotypes and prejudice together (Model 3), as well as racial stereotypes and prejudice, controlling for county demographics (Models 4 and 5).

Predictor	Model 1				Model 2				Model 3				Model 4				Model 5			
	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p
Intercept	4.52	[1.73, 7.32]	3.17	.002	4.68	[2.08, 7.28]	3.53	< .001	3.86	[-1.19, 8.92]	1.50	.135	4.82	[-0.08, 9.73]	1.93	.054	-5.59	[-11.23, 0.05]	-1.94	.053
Weapons IAT	-3.29	[-10.14, 3.55]	-0.94	.346					-3.37	[-10.20, 3.45]	-0.97	.333	-3.38	[-9.78, 3.03]	-1.03	.302	-2.86	[-9.43, 3.71]	-0.85	.394
S Harmless	0.63	[-2.83, 4.08]	0.36	.723					0.87	[-2.59, 4.32]	0.49	.624	2.48	[-0.79, 5.74]	1.49	.137	2.16	[-1.19, 5.50]	1.26	.207
S Weapons	1.55	[-0.52, 3.62]	1.47	.143					0.21	[-1.96, 2.38]	0.19	.849	0.83	[-1.22, 2.88]	0.79	.429	0.78	[-1.32, 2.88]	0.73	.465
Race IAT					-3.97	[-9.97, 2.04]	-1.29	.196	3.05	[-8.53, 14.62]	0.52	.606	4.87	[-6.06, 15.80]	0.87	.383	3.05	[-8.12, 14.22]	0.54	.592
Self-rep. prejudice					0.59	[0.27, 0.92]	3.56	< .001	1.07	[0.48, 1.66]	3.57	< .001	1.63	[1.06, 2.21]	5.55	< .001	1.41	[0.83, 1.99]	4.74	< .001
% Black population													-0.17	[-0.21, -0.14]	-9.04	< .001				
% White population																	0.11	[0.08, 0.14]	6.98	< .001

Note: Weapons IAT = Weapons IAT *D* score; S Harmless Objects = self-reported rating of how much harmless objects are associated with Black and White people; S Weapons = self-reported rating of how much weapons are associated with Black and White people; Race IAT = Evaluative Race IAT *D* score; Self-rep. prejudice = combined score of measures of self-reported prejudice (i.e., preference for Whites and feeling thermometer difference score). For these models, number of respondents per county is not restricted.

Table S5

Counties with more than 50 respondents: Racial disparities in police traffic stops predicted by racial stereotypes (Model 1), racial prejudice (Model 2), racial stereotypes and prejudice together (Model 3), as well as racial stereotypes and prejudice, controlling for county demographics (Models 4 and 5).

Predictor	Model 1			Model 2			Model 3			Model 4			Model 5		
	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t
Intercept	4.53	[0.57, 8.49]	2.24	.026	3.68	[0.20, 7.16]	2.07	.039	3.96	[-3.20, 11.11]	1.08	.279	5.90	[-0.91, 12.71]	1.70
Weapons IAT	-2.99	[-13.50, 7.52]	-0.56	.577					-3.45	[-13.91, 7.01]	-0.65	.518	-3.97	[-13.72, 5.79]	-0.80
S Harmless	0.17	[-5.02, 5.37]	0.07	.948					0.24	[-4.91, 5.38]	0.09	.928	2.50	[-2.32, 7.32]	1.02
S Weapons	1.13	[-2.05, 4.31]	0.70	.487					-1.25	[-4.58, 2.07]	-0.74	.461	-0.64	[-3.77, 2.50]	-0.40
Race IAT					-0.77	[-9.30, 7.75]	-0.18	.859	3.73	[-13.27, 20.72]	0.43	.667	4.00	[-11.93, 19.92]	0.49
Self-rep. prejudice					0.67	[0.29, 1.04]	3.47	.001	1.40	[0.72, 2.09]	4.01	< .001	1.80	[1.14, 2.46]	5.34
% Black population													-0.19	[-0.23, -0.14]	-8.30
% White population															

Note: Weapons IAT = Weapons IAT D score; S Harmless Objects = self-reported rating of how much harmless objects are associated with Black and White people; S Weapons = self-reported rating of how much weapons are associated with Black and White people; Race IAT = Evaluative Race IAT D score; Self-rep. prejudice = combined score of measures of self-reported prejudice (i.e., preference for Whites and feeling thermometer difference score). Models are restricted to more than 50 respondents per county.

0.11

[0.08, 0.15]

6.21

< .001

Table S6

Countries with more than 75 respondents: Racial disparities in police traffic stops predicted by racial stereotypes (Model 1), racial prejudice (Model 2), racial stereotypes and prejudice together (Model 3), as well as racial stereotypes and prejudice, controlling for county demographics (Models 4 and 5).

Predictor	Model 1				Model 2				Model 3				Model 4				Model 5			
	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p
Intercept	4.53	[0.57, 8.49]	2.24	.037	2.68	[-1.32, 6.68]	1.31	.189	5.26	[-3.74, 14.27]	1.15	.253	8.01	[-0.36, 16.39]	1.87	.062	-3.78	[-12.87, 5.31]	-0.82	.415
Weapons IAT	-2.99	[-13.50, 7.52]	-0.56	.468					-6.73	[-21.09, 7.64]	-0.92	.359	-2.02	[-15.11, 11.06]	-0.30	.762	-2.38	[-16.06, 11.31]	-0.34	.734
S Harmless	0.17	[-5.02, 5.37]	0.07	.280					4.17	[-2.67, 11.01]	1.19	.233	8.37	[2.09, 14.66]	2.61	.009	7.17	[0.61, 13.73]	2.14	.033
S Weapons	1.13	[-2.05, 4.31]	0.70	.071					1.00	[-3.33, 5.32]	0.45	.652	1.51	[-2.49, 5.50]	0.74	.460	1.68	[-2.48, 5.83]	0.79	.429
Race IAT					2.33	[-7.50, 12.16]	0.47	.642	3.97	[-17.14, 25.07]	0.37	.713	-0.93	[-20.23, 18.37]	-0.09	.925	-3.61	[-23.81, 16.59]	-0.35	.726
Self-rep. prejudice					0.76	[0.36, 1.16]	3.74	< .001	1.24	[0.44, 2.04]	3.05	.002	1.79	[1.03, 2.55]	4.62	< .001	1.61	[0.83, 2.40]	4.04	< .001
% Black population													-0.22	[-0.26, -0.17]	-8.82	< .001				
% White population																	0.13	[0.09, 0.17]	6.36	< .001

Note: Weapons IAT = Weapons IAT D score; S Harmless Objects = self-reported rating of how much harmless objects are associated with Black and White people; S Weapons = self-reported rating of how much weapons are associated with Black and White people; Race IAT = Evaluative Race IAT D score; Self-rep. prejudice = combined score of measures of self-reported prejudice (i.e., preference for Whites and feeling thermometer difference score). Models are restricted to more than 75 respondents per county.

Table S7

Counties with more than 100 respondents: Racial disparities in police traffic stops predicted by racial stereotypes (Model 1), racial prejudice (Model 2), racial stereotypes and prejudice together (Model 3), as well as racial stereotypes and prejudice, controlling for county demographics (Models 4 and 5).

Predictor	Model 1				Model 2				Model 3				Model 4				Model 5			
	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p
Intercept	5.07	[-0.67, 10.81]	1.73	.084	2.46	[-1.99, 6.90]	1.08	.280	-0.03	[-10.24, 10.18]	-0.01	.995	5.70	[-3.78, 15.18]	1.18	.240	-7.84	[-17.87, 2.19]	-1.53	.126
Weapons IAT	-5.99	[-22.32, 10.34]	-0.72	.473					-7.93	[-24.37, 8.51]	-0.95	.345	-4.84	[-19.62, 9.93]	-0.64	.521	-3.06	[-18.56, 12.45]	-0.39	.700
S Harmless	-1.53	[-9.69, 6.63]	-0.37	.713					-0.76	[-8.95, 7.43]	-0.18	.856	6.02	[-1.51, 13.55]	1.57	.118	5.89	[-2.09, 13.86]	1.45	.149
S Weapons	2.43	[-1.94, 6.81]	1.09	.276					-0.39	[-5.08, 4.30]	-0.16	.871	1.39	[-2.93, 5.71]	0.63	.528	1.18	[-3.31, 5.67]	0.51	.607
Race IAT					2.94	[-8.10, 13.98]	0.52	.602	17.09	[-7.34, 41.51]	1.37	.171	6.83	[-15.54, 29.21]	0.60	.550	4.89	[-18.52, 28.30]	0.41	.682
Self-rep. prejudice					0.63	[0.20, 1.05]	2.89	.004	0.72	[-0.16, 1.61]	1.61	.109	1.52	[0.68, 2.37]	3.55	< .001	1.36	[0.49, 2.23]	3.06	.002
% Black population													-0.22	[-0.27, -0.17]	-8.73	< .001				
% White population																	0.14	[0.10, 0.18]	6.51	< .001

Note: Weapons IAT = Weapons IAT D score; S Harmless Objects = self-reported rating of how much harmless objects are associated with Black and White people; S Weapons = self-reported rating of how much weapons are associated with Black and White people; Race IAT = Evaluative Race IAT D score; Self-rep. prejudice = combined score of measures of self-reported prejudice (i.e., preference for Whites and feeling thermometer difference score). Models are restricted to more than 100 respondents per county.

Table S8

Countries with more than 150 respondents: Racial disparities in police traffic stops predicted by racial stereotypes (Model 1), racial prejudice (Model 2), racial stereotypes and prejudice together (Model 3), as well as racial stereotypes and prejudice, controlling for county demographics (Models 4 and 5).

Predictor	Model 1			Model 2			Model 3			Model 4			Model 5		
	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t	p	Beta	95% CI	t
Intercept	4.53	[0.57, 8.49]	2.24	.175	1.35	[-4.15, 6.84]	0.48	.631	0.08	[-12.39, 12.54]	0.01	.991	6.92	[-4.36, 18.20]	1.20
Weapons IAT	-2.99	[-13.50, 7.52]	-0.56	.541					-8.95	[-29.15, 11.26]	-0.87	.386	-3.88	[-21.74, 13.98]	-0.43
S Harmless	0.17	[-5.02, 5.37]	0.07	.867					0.62	[-9.85, 11.08]	0.12	.908	9.78	[0.26, 19.31]	2.01
S Weapons	1.13	[-2.05, 4.31]	0.70	.104					1.07	[-4.87, 7.00]	0.35	.725	3.47	[-1.93, 8.87]	1.26
Race IAT					6.16	[-7.72, 20.03]	0.87	.385	17.62	[-13.19, 48.43]	1.12	.263	4.29	[-23.26, 31.84]	0.31
Self-rep. prejudice					0.90	[0.40, 1.39]	3.54	< .001	0.72	[-0.38, 1.82]	1.28	.202	1.84	[0.81, 2.87]	3.50
% Black population													-0.25	[-0.31, -0.19]	-8.55
% White population															

Note: Weapons IAT = Weapons IAT *D* score; S Harmless Objects = self-reported rating of how much harmless objects are associated with Black and White people; S Weapons = self-reported rating of how much weapons are associated with Black and White people; Race IAT = Evaluative Race IAT *D* score; Self-rep. prejudice = combined score of measures of self-reported prejudice (i.e., preference for Whites and feeling thermometer difference score). Models are restricted to more than 150 respondents per county.

0.15

[0.11, 0.20]

6.29

< .001

Figure S2. Comparison of outlier criteria: Zero-order correlations between county-level disproportionate stopping of Black drivers and county-level measures of White residents' racial stereotypes and prejudice after removing outlier defined as 3, 2.5 and 2 standard deviations above and below the county-level average in disproportionate stopping of Black drivers.

Table S9

Descriptive statistics of Black residents' racial stereotype and prejudice measures

	Exclusion criteria	M	SD	N (counties)	t	p	d	95% CI	N (respondents)
Weapons IAT	All counties	0.23	0.27	1,413	32.24	< .001	0.82	[0.76, 0.87]	23,885
	> 25 respondents	0.20	0.06	803	52.16	< .001	3.05	[2.78, 3.32]	20,578
	> 50 respondents	0.19	0.05	747	50.52	< .001	3.73	[3.32, 4.14]	18,641
	> 75 respondents	0.19	0.04	717	51.29	< .001	4.46	[3.89, 5.02]	16,775
	> 100 respondents	0.18	0.04	707	49.28	< .001	4.90	[4.18, 5.60]	15,922
Stereotype Harmless	> 150 respondents	0.18	0.04	685	38.97	< .001	4.76	[3.91, 5.59]	13,153
	All counties	0.09	0.70	3,050	5.33	< .001	-0.13	[0.08, 0.18]	40,241
	> 25 respondents	0.10	0.14	276	11.78	< .001	-0.71	[0.58, 0.84]	33,783
	> 50 respondents	0.11	0.11	170	12.64	< .001	-0.97	[0.79, 1.15]	30,020
	> 75 respondents	0.11	0.09	123	12.72	< .001	-1.15	[0.92, 1.37]	27,056
Stereotype Weapons	> 100 respondents	0.12	0.09	94	12.79	< .001	-1.32	[1.04, 1.59]	24,573
	> 150 respondents	0.13	0.08	64	12.75	< .001	-1.59	[1.22, 1.96]	20,865
	All counties	0.08	0.97	3,050	3.24	.001	0.08	[0.03, 0.13]	40,726
	> 25 respondents	0.04	0.25	280	2.97	.003	0.18	[0.06, 0.30]	34,287
	> 50 respondents	0.07	0.20	170	4.43	< .001	0.34	[0.18, 0.49]	30,381
Race IAT	> 75 respondents	0.04	0.17	123	2.72	.007	0.25	[0.07, 0.42]	27,384
	> 100 respondents	0.02	0.16	95	1.40	.164	0.14	[-0.06, 0.35]	24,973
	> 150 respondents	0.03	0.15	65	1.47	.147	0.18	[-0.06, 0.43]	21,270
	All counties	-0.03	0.23	1,413	-4.23	< .001	0.09	[-0.13, -0.05]	224,116
	> 25 respondents	-0.04	0.07	795	-18.06	< .001	0.60	[-0.67, -0.53]	219,377
Preference for Whites	> 50 respondents	-0.04	0.05	667	-17.95	< .001	0.69	[-0.77, -0.61]	214,776
	> 75 respondents	-0.04	0.05	617	-18.08	< .001	0.76	[-0.86, -0.67]	211,780
	> 100 respondents	-0.03	0.04	579	-16.78	< .001	0.76	[-0.86, -0.66]	208,367
	> 150 respondents	-0.03	0.03	521	-17.51	< .001	0.89	[-1.01, -0.77]	201,174
	All counties	-0.76	0.73	3,126	-50.46	< .001	1.04	[-1.09, -0.99]	356,344
Feeling Thermometer	> 25 respondents	-0.90	0.20	855	-130.34	< .001	4.46	[-4.68, -4.23]	345,760
	> 50 respondents	-0.91	0.17	630	-137.74	< .001	5.49	[-5.80, -5.17]	337,508
	> 75 respondents	-0.92	0.15	537	-140.25	< .001	6.05	[-6.42, -5.68]	331,777
	> 100 respondents	-0.93	0.15	451	-132.94	< .001	6.26	[-6.68, -5.84]	324,255
	> 150 respondents	-0.94	0.13	365	-138.16	< .001	7.23	[-7.76, -6.69]	313,801
Feeling Thermometer	All counties	-0.39	0.39	3,126	-48.94	< .001	1.01	[-1.06, -0.96]	373,337
	> 25 respondents	-0.47	0.10	879	-135.11	< .001	4.56	[-4.78, -4.33]	362,804
	> 50 respondents	-0.48	0.08	646	-148.02	< .001	5.82	[-6.15, -5.49]	354,324
	> 75 respondents	-0.48	0.08	548	-147.19	< .001	6.29	[-6.67, -5.90]	348,321
	> 100 respondents	-0.48	0.07	468	-145.26	< .001	6.71	[-7.15, -6.27]	341,296
Feeling Thermometer	> 150 respondents	-0.49	0.06	369	-147.15	< .001	7.66	[-8.22, -7.09]	329,136

Note. Weapons IAT = Weapons IAT D score; Stereotype Harmless = self-reported rating of how much harmless objects are associated with Black and White people; Stereotype Weapons = self-reported rating of how much weapons are associated with Black and White people; Race IAT = Evaluative Race IAT D score; Preference for Whites = preference for Whites relative to Blacks on one-item preference measure; feeling Thermometer = Feeling thermometer difference score for Whites relative to Blacks; positive scores on racial prejudice and stereotype measures indicate less favorable evaluations and more negative stereotypes of Blacks relative to Whites, whereas negative scores on racial prejudice and stereotype measures indicate more favorable evaluations and less negative stereotypes of Blacks relative to Whites. All measures were tested with two-sided one-sample t-tests against zero.

Figure S3. Zero-order correlations between county-level measures of Black residents' racial stereotypes and prejudice and county-level disproportionate stopping of Black drivers.

Table S10

Zero-order correlations between Black residents' racial stereotypes and prejudice and disproportionate stopping of Black drivers

		1	2	3	4	5	6	7
1. Disproportionate Stops	All counties	-	749	762	760	1083	1080	1089
	Counties with > 25 respondents	-	164	156	157	490	461	472
	Counties with > 50 respondents	-	104	95	97	358	333	340
	Counties with > 75 respondents	-	74	72	72	304	296	298
	Counties with > 100 respondents	-	63	61	62	267	248	259
2. Weapons IAT	Counties with > 150 respondents	-	63	61	62	267	248	259
	All counties	-.07	-	746	745	732	732	734
	Counties with > 25 respondents	.06	-	156	157	164	164	164
	Counties with > 50 respondents	.11	-	95	97	104	104	104
	Counties with > 75 respondents	.15	-	72	72	74	74	74
3. Stereotype Harmless	Counties with > 100 respondents	.13	-	61	62	63	63	63
	Counties with > 150 respondents	.06	-	39	39	42	42	42
	All counties	-.04	-.03	-	760	745	745	747
	Counties with > 25 respondents	-.05	.00	-	156	156	156	156
	Counties with > 50 respondents	-.11	-.17	-	95	95	95	95
4. Stereotype Weapons	Counties with > 75 respondents	-.11	-.09	-	72	72	72	72
	Counties with > 100 respondents	-.09	-.02	-	61	61	61	61
	Counties with > 150 respondents	-.17	-.14	-	39	39	39	39
	All counties	-.04	.13***	-.04	-	744	744	746
	Counties with > 25 respondents	-.13	.25**	-.11	-	157	157	157
5. Race IAT	Counties with > 50 respondents	-.09	.15	-.11	-	97	97	97
	Counties with > 75 respondents	-.13	.24*	-.09	-	72	72	72
	Counties with > 100 respondents	-.23	.21	-.07	-	62	62	62
	Counties with > 150 respondents	-.34*	.20	.05	-	39	39	39
	All counties	.00	.01	-.10**	.01	-	1072	1080
6. Preference for Whites	Counties with > 25 respondents	.08	.23**	-.25**	-.05	-	461	472
	Counties with > 50 respondents	.07	.10	-.38***	-.14	-	333	340
	Counties with > 75 respondents	.06	.15	-.25*	-.16	-	296	298
	Counties with > 100 respondents	.03	.15	-.34**	-.09	-	248	259
	Counties with > 150 respondents	.06	.24	-.49**	-.29	-	197	199
7. Feeling Thermometer	All counties	.00	.04	-.07*	.05	.20***	-	1080
	Counties with > 25 respondents	.00	.20*	-.14	-.13	.37***	-	461
	Counties with > 50 respondents	.00	.15	-.17	-.02	.46***	-	333
	Counties with > 75 respondents	.03	.17	-.18	-.03	.47***	-	296
	Counties with > 100 respondents	.00	.16	-.21	.05	.46***	-	248
	Counties with > 150 respondents	.01	.17	-.30	.10	.47***	-	197
	All counties	-.05	.06	-.05	.01	.16***	.62***	-
	Counties with > 25 respondents	-.03	.22**	-.06	-.04	.20***	.69***	-
	Counties with > 50 respondents	.01	.17	-.11	.04	.35***	.70***	-
	Counties with > 75 respondents	.00	.16	-.18	.08	.39***	.75***	-
	Counties with > 100 respondents	.03	.14	-.15	.10	.38***	.84***	-
	Counties with > 150 respondents	.06	.12	-.31	.14	.35***	.86***	-

Note. * $p < .05$; ** $p < .01$; *** $p < .001$; values in the lower triangle represent correlation coefficients; values in the upper triangle represent number of pair-wise cases (i.e., number of counties).