On Historical Sundown Towns and Racial Bias

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Abstract

Sundown towns refer to places that restricted or excluded the movement or settlement of racial and ethnic minorities. Though civil rights legislation largely put an end to their official aspects, the cultural legacy of sundown towns may persist today within geographical regions. In the present research, we examined whether the geographic distribution of sundown towns in the United States is evident in regional aggregates of the racial biases of modern-day residents. Using the geolocated responses of more than 1.3 million people, we found that counties characterized in the past by sundown policies or the presence of sundown towns have higher levels of implicit and explicit bias today. These findings are consistent across pre-registered robustness checks, but exploratory analyses highlight potential boundary conditions. This research integrates social, historical, and geographical psychology to demonstrate that the effects of a shameful period in United States history still persists today.

KEYWORDS: racial bias, geographic psychology, historical psychology

On Sundown Towns and Racial Bias

Sundown towns refer to places that restricted or excluded the movement or settlement of racial and ethnic minorities within their borders. Local governments enacted ordinances prohibiting Black people from purchasing or renting properties. Law enforcement harassed Black people who were in town after dark, and locals intimidated, attacked, and sometimes even lynched Black people who were found outdoors after sundown (Loewen, 2005). Sundown towns date back to the colonial era in the United States and remained until the 1980s, by which time civil rights legislation had largely put an end to their official aspects (e.g., ordinances, harassment from law enforcement). However, the cultural legacy of sundown towns may still persist today within geographical regions. In the present research, we examine whether the cultural legacies of sundown towns are evident in regional aggregates of the racial biases of modern-day residents.

Our research is grounded in situational models of bias (Calanchini et al., 2022; Murphy & Walton, 2013; Murphy et al., 2018; Payne et al., 2017). Situational models argue that bias is a product of, and persists in, the environments we inhabit. Environments can refer to physical locations as well as social and cultural contexts. A growing literature linking environments with intergroup biases supports this perspective (Charlesworth & Banaji, 2022; Goedderz & Calanchini, 2023; Hehman et al., 2018; Ofosu et al., 2019; Payne et al., 2019; Primbs et al., 2024a; Primbs et al., 2024b; Primbs et al., 2025; Vuletich & Payne, 2019; Vuletich et al., 2024). Quite naturally, environments are defined by their histories: Some places hosted Nazi concentration camps, hold reminders of past genocides, or were built on the backs of slaves. Situational models of bias argue that physical and cultural reminders of such histories shape the biases of people currently living in these places (Payne & Hannay, 2021).

Empirical research linking historical inequalities with the biases of present-day populations supports these assertions (Payne et al., 2019; Primbs et al., 2024b; Vuletich et al., 2024; Vuletich & Payne, 2019). Research on the historical legacy of slavery found that present-day residents of areas that more strongly relied on slaves in 1860 are more racially biased today (Payne et al., 2019). Likewise, people in regions inhabited by a higher proportion of Black people during the Great Migration – a period in United States history during which many Black people migrated from the South to northern states – show higher levels of contemporary racial bias (Vuletich et al., 2024). Here, we argue that the same types of cultural processes through which the historical legacies of slavery and the Great Migration persist also maintain the historical legacy of sundown towns. Consequently, the historical presence of sundown towns in a region should be associated with higher modern levels of racial bias.

We adopt a multiverse approach to test this idea. First, we investigate whether the presence of a sundown town in a county is associated with higher levels of aggregate implicit (Hypothesis 1a) and explicit (Hypothesis 1b) racial bias compared to counties with no sundown towns. Second, we test whether the number of sundown towns in a county is associated with higher levels of aggregate implicit (Hypothesis 2a) and explicit (Hypothesis 2b) racial bias. Just as some towns were designed as sundown, so too were some counties characterized by exclusionary norms and policies. Thus, our third and final set of analyses investigates whether sundown counties are associated with higher levels of aggregate implicit (Hypothesis 3a) and explicit (Hypothesis 3b) racial bias.

Our research integrates traditional social psychology with both geographical (Calanchini et al., 2022; Götz et al., 2025) and historical psychology (Atari et al., 2025; Trawalter et al., 2022). If the psychological legacy of a racist past lingers for generations within regions, what does that mean for our understanding of how intergroup bias forms and changes? Linking past social, cultural, and physical environments to modern-day psychologies can contribute to a fuller understanding of human psychology.

Methods

Transparency Statement

We pre-registered our hypotheses, datasets, exclusion criteria, and analyses on the OSF (https://osf.io/j4gp6/?view_only=65d9064e428a4b7c878509e96b8de2fe). Our main analyses do not deviate from our pre-registered analyses. However, we deviate from the pre-registered analyses in one of the robustness checks, due to unforeseeable issues with the data. We clearly mark this in the results section. We make all our processed data and analysis code freely available (https://osf.io/d5f3b/?view_only=bb2d57a4b3d24f3dbfce97250f75f4a8).

Datasets and Measures

This study combined the 2002 to 2024 subset of the race data from Project Implicit (Xu et al., 2022). Previous research describes this Project Implicit dataset in detail (Charlesworth & Banaji, 2019, 2021, 2022). For theoretical precision, we restricted our analyses to White participants with complete IAT data who provided information about the county in which they currently live, and who are located on the United States mainland. We further removed all participants who responded faster than 300ms on more than 10% of IAT trials. We pre-registered these exclusion criteria (https://osf.io/j4gp6/?view_only=65d9064e428a4b7c878509e96b8de2fe). Our final dataset contains the responses of 1,372,688 participants, of whom 673,191 live in counties with a sundown town and 699,497 live in counties without a sundown town. Further, 28,941 participants live in counties designated as sundown counties and 1,342,847 in counties not designated as sundown counties.

Implicit Racial Bias

We operationalized implicit bias in terms of responses to the evaluate race IAT (Greenwald et al., 1998), as implemented at Project Implicit (https://implicit.harvard.edu/implicit/). In the evaluative race IAT, participants categorize faces as African American (here referred to as Black) or European American (here referred to as White) and words as positive or negative. We calculated IAT D-Scores (Greenwald et al., 2003) following the Project Implicit algorithm and interpreted higher IAT D-Scores as reflecting higher levels of pro-White/anti-Black racial bias. The IAT has been critiqued as a measure of individual differences (e.g., Blanton et al., 2009, 2015). However, in the present research we rely on IAT responses that have been aggregated to geographical levels, which addresses many of these criticisms (Calanchini et al., 2022; Hehman et al., 2019). Figure 1 shows the distribution of race IAT scores across the United States.

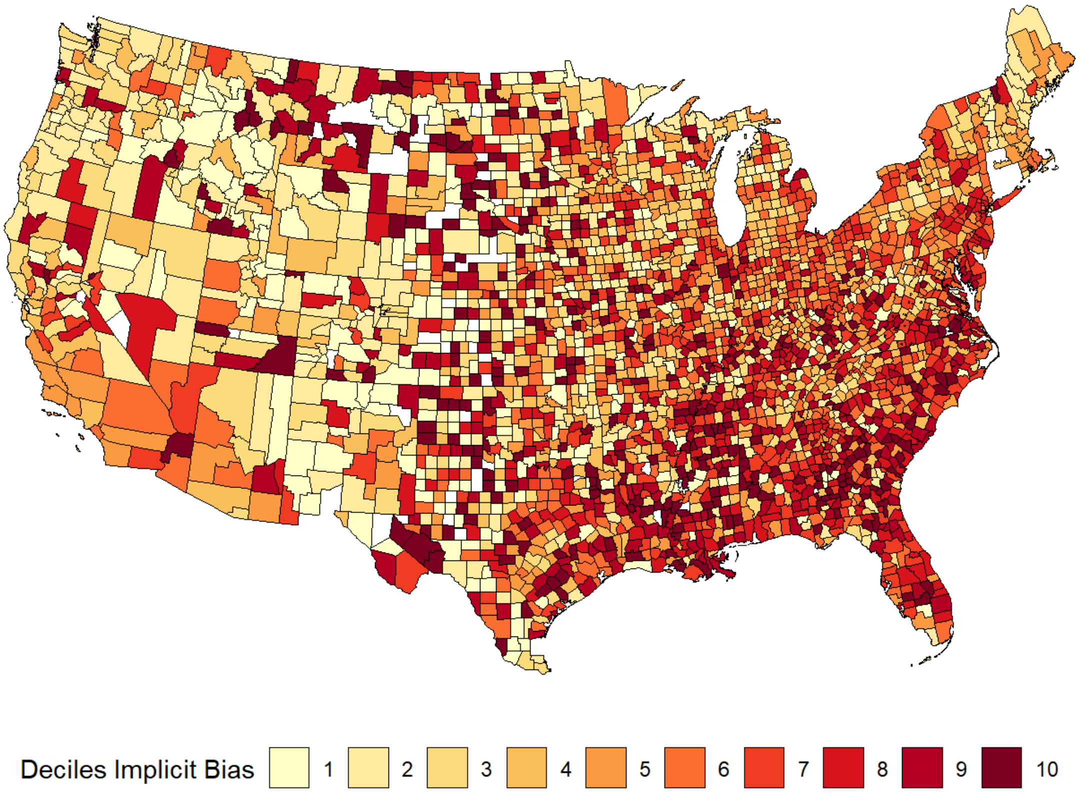

Figure 1. This map shows the distribution of county-level Race IAT scores throughout the continental United States. Darker regions reflect stronger pro-White / anti-Black racial bias.

Explicit Racial Bias

Participants reported how warm or cold they feel towards White and, separately, Black people, on an 11-point Likert scale ranging from "*Extremely Cold*" to "*Extremely Warm*". From these feeling thermometer ratings we calculated differences scores by subtracting the ratings for Black people from the ratings for White people. Analogous to the IAT D-Score, more positive scores reflect stronger pro-White / anti-Black racial bias. Figure 2 shows the distribution of explicit bias scores across the United States.

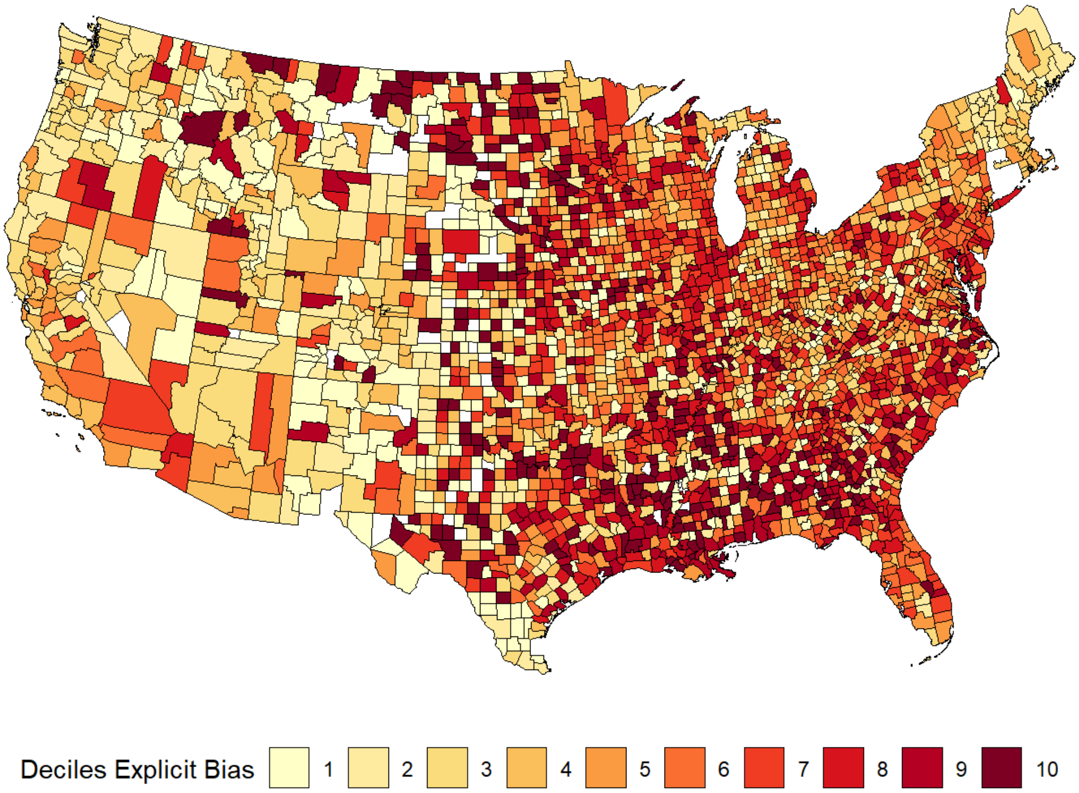

Figure 2. This map shows the distribution of county-level explicit bias scores throughout the continental United States. Darker regions reflect stronger pro-White / anti-Black racial bias.

Sundown Towns

We obtained information about sundown towns from Rigby and colleagues (2025) who provide information about historical sundown towns across the entirety of the United States. They defined sundown towns as places where a set of legal or informal practices restricted the mobility and settlement of racial or ethnic minorities. The designation of a place as sundown was based on historical work by Loewen (2005) and Berrey (2024), who combined interviews with community members with analyses of historical documents (e.g., newspaper articles) and census data.

We aggregated Rigby and colleagues' (2025) data to the county level, and for each recorded the presence of a sundown town in the county (H1) and the number of sundown towns per county (H2). Moreover, the database also contained records on sundown counties – places where a whole county has been designated a sundown area (H3). Figure 3 shows the distribution of counties with sundown towns, Figure 4 the number of sundown towns per county, and Figure 5 the distribution of counties with sundown designation.

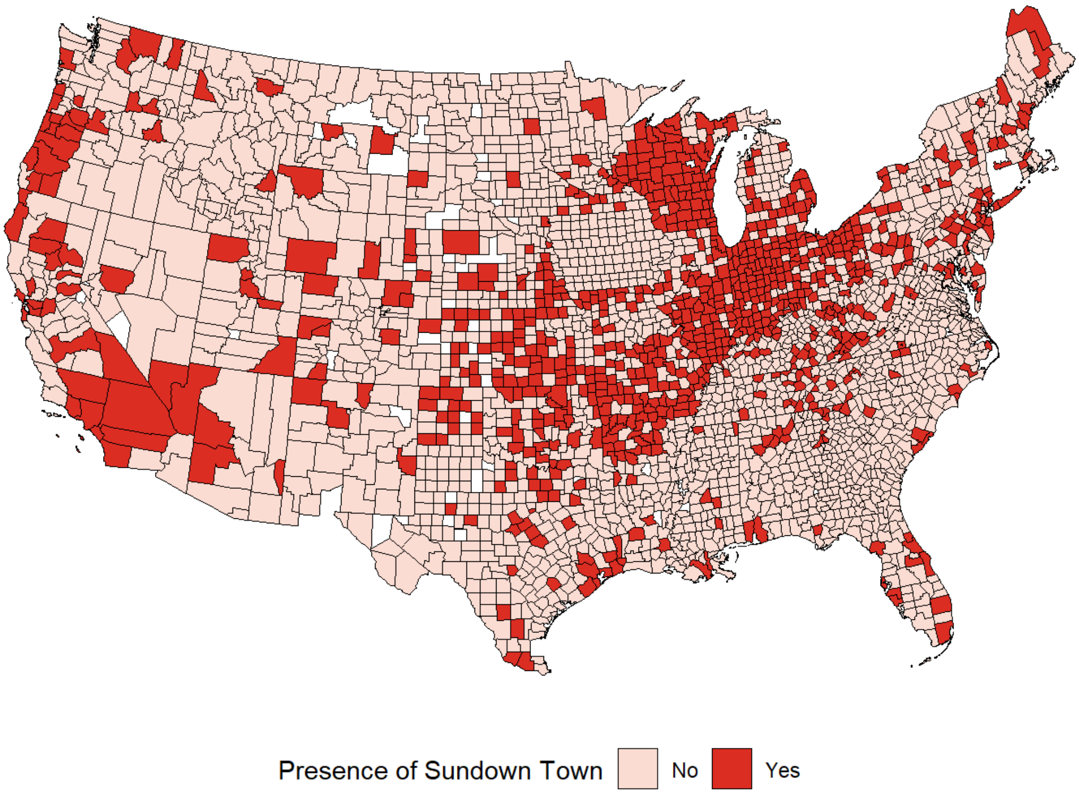

Figure 3. This map shows the distribution of counties with at least one sundown town throughout the continental United States.

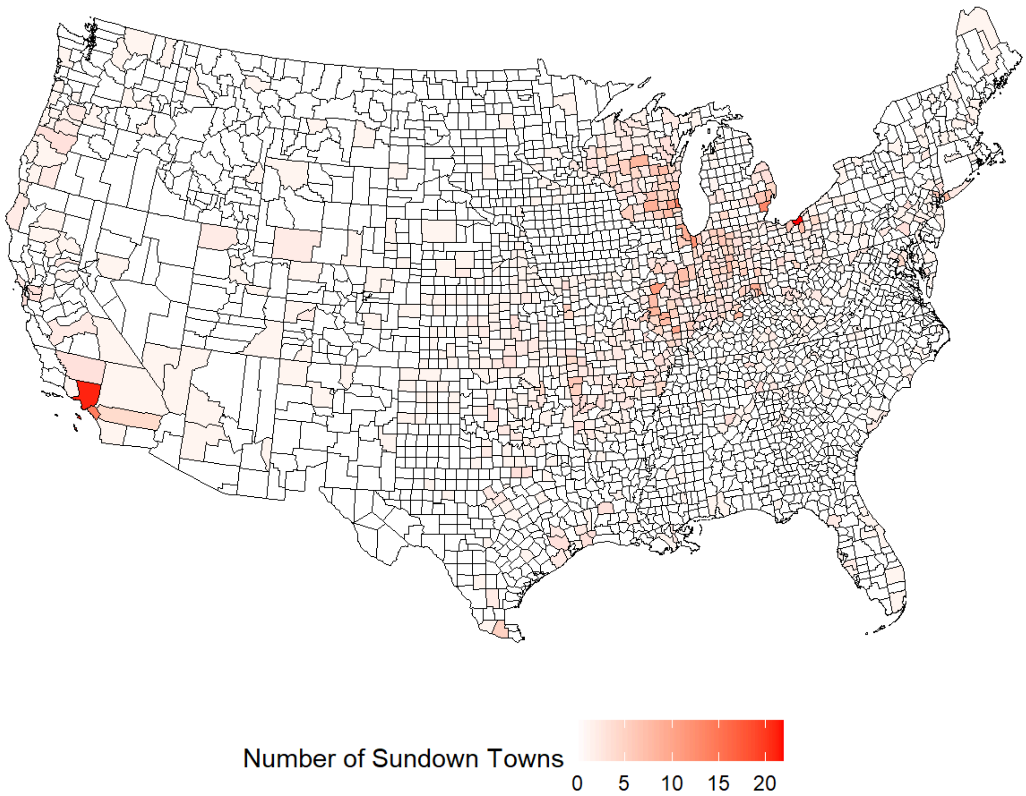

Figure 4. This map shows the number of sundown towns per county throughout the continental United States. Darker regions indicate more sundown towns. Most counties have a relatively small number of sundown towns, but a few counties have many sundown towns.

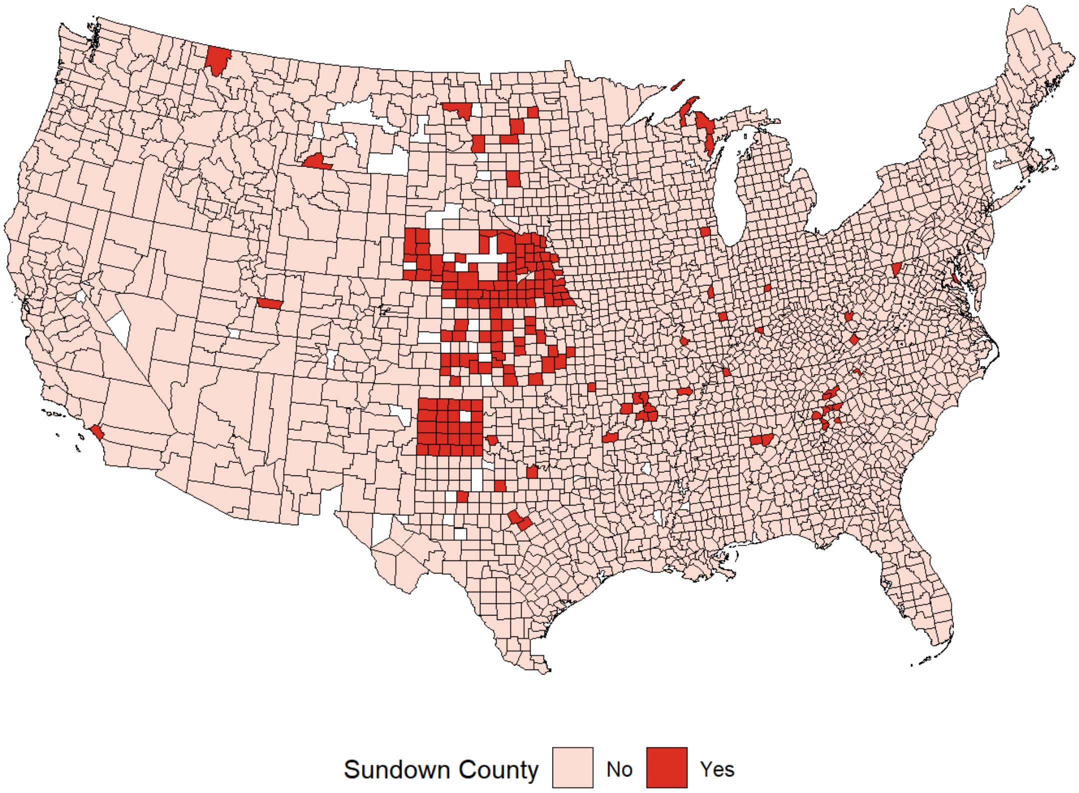

Figure 5. This map shows the distribution of sundown counties throughout the continental United States.

Control Variables

We included population density, the proportion of Black people living in a county, education (i.e., the proportion of people aged 25 or older with a high school degree), and income (i.e., median household income over the past 12 months) as control variables. All control variables reflect 5-year estimates (2018-2022) from the American Community Survey (United States Census Bureau, 2024). We pre-registered our choice of covariates.

Analyses

We pre-registered our main analyses (https://osf.io/j4gp6/?view_only=65d9064e428a4b7c878509e96b8de2fe). For each hypothesis, we ran a linear regression with presence of a sundown town in a county (H1), number of sundown towns per county (H2) or designation of a whole county as sundown county (H3) as focal predictor; population density, proportion of Black population, education levels, and income as covariates; and implicit (H1a, H2a, H3a) or explicit (H1b, H2b, H3b) bias as dependent variable. Each model was weighted according to the number of Project Implicit respondents per county. As pre-registered, we ran each model once with untransformed covariates, and again with log-transformed covariates to address skewness.

Geographical data like the data we analysed here often have spatial dependencies: Areas that are closer together are often more similar to each other because of mutual interdependence, which can violate the independence assumptions that underpin most statistical modeling approaches. Models that fail to account for such spatial clustering often produce biased estimates (Anselin, 1988; Ebert et al., 2023). Spatial regression models can correct for these spatial dependencies. Here, we used two different types of spatial regression models: Spatial lag and spatial error models. Spatial lag models assume that spatial dependencies represent meaningful information about adjacent counties affecting each other. Spatial error models assume that spatial dependencies reflect noise (Ebert et al., 2023). Because we cannot make definitive claims about the nature of spatial dependencies, we here report results for both spatial lag and spatial error models.

To that end, we assessed spatial clustering in the residuals of each linear regression using a permutation-based Moran's test implemented in the package spdep (version 1.3.3; Bivand & Wong, 2018). For each model, if we found evidence of spatial dependence in the form of a statistically-significant Moran's test (i.e., $p < .05$), we ran spatial regression analyses. If Moran's test did not indicate evidence of spatial dependence, we calculated and interpreted the marginal effects[1] using the marginaleffects package (version 0.21.0;

[1]Regression coefficients from complex models are often not interpretable and researchers need to further query the model in order to obtain meaningful answers to their questions. Marginal effects state how much the dependent variable changed in response to changes in the independent variable. Thus, marginal effects are one

Arel-Bundock et al., 2024). Throughout this manuscript we only interpret models that showed no evidence of spatial dependencies.

To set up the spatial regressions, we first created spatial weights matrices using k-nearest neighbour weights. We implemented the spatial lag and spatial error models using k-nearest neighbour-based spatial weight matrices. The spatial regressions included the same covariates, predictors, and dependent variables as the linear regressions. We implemented all spatial regressions with the spatialreg package (Version 1.3.2, Bivand et al., 2013), aided by the sf package (version 1.0.14; Pebesma, 2018; Pebesma & Bivan, 2023). Finally, for each spatial model, we used Moran's test on the residuals of the spatial regressions to assess whether the spatial regressions successfully reduced the spatial autocorrelation. In addition to the pre-registered analyses, we present the results of several exploratory analyses in the supplementary materials (S1: models without covariates; S2: unweighted linear regressions; S3: alternative inclusion thresholds; S4: more restrictive inclusion criteria), which we summarize below.

Results

We pre-registered a set of confirmatory analyses to test H1-3. We summarize our findings here in the main text and report details in Table 1[2]. We found support for H1a, such that the presence of a sundown town in a county is associated with higher levels of implicit racial bias. This effect held for both raw and log-transformed covariates, and we found no evidence of spatial autocorrelation. We found the same pattern of results for H1b, though the evidence was less consistent. Significant positive relationships emerged between the presence of a sundown town in a county and explicit racial bias even when we accounted for spatial autocorrelation, in the models with log-transformed but not raw covariates.

way for researchers to obtain interpretable answers from complex models (Rohrer, 2022 and Rohrer & Arel-Bundock, 2025). Our use of the term 'marginal' does not refer to marginal statistical significance."

[2] We only report R^2 values for the linear models because they do not apply to spatial models.

We found even more consistent relationships in the models testing H3. Counties designated as sundown are associated with higher levels of implicit bias (H3a). This effect held for both raw and log-transformed covariates, and we found no evidence of spatial autocorrelation. Counties designated as sundown are associated with higher levels of explicit bias (H3b), and this effect persisted across models with raw and log-transformed covariates, and accounting for spatial autocorrelation. No evidence emerged for either H2a or H2b: the number of sundown towns in a county was unrelated to either implicit or explicit racial bias.

Table 1

Summary of Statistical Models: Race

Hypothesis	Analysis	Covariates	R^2	Coefficient	*SE*	*p*	*Moran's p*
Hypothesis 1: Presence of a sundown town in a county							
Implicit	**Linear Model**	**Raw**	.196	**0.005**	**0.001**	**<.001**	**.104**
	Linear Model	**Log**	.281	**0.004**	**0.001**	**<.001**	**.218**
Explicit	Linear Model	Raw	.211	0.048	0.007	<.001	.001
	Linear Model	Log	.283	0.060	0.007	<.001	.001
	Spatial Lag	**Raw**		**0.041**	**0.023**	**.075**	**.793**
	Spatial Error	**Raw**		**0.043**	**0.024**	**.074**	**.629**
	Spatial Lag	**Log**		**0.048**	**0.024**	**.045**	**.809**
	Spatial Error	**Log**		**0.048**	**0.025**	**.049**	**.590**

Hypothesis 2: Number of sundown towns per county							
Implicit	**Linear Model**	**Raw**	.192	**0**	**0**	**.141**	**.109**
	Linear Model	**Log**	.279	**0**	**0**	**.122**	**.225**
Explicit	Linear Model	Raw	.201	0.002	0.001	.008	.001
	Linear Model	Log	.272	0.004	0.001	<.001	.001
	Spatial Lag	**Raw**		**0.010**	**0.008**	**.202**	**.798**
	Spatial Error	**Raw**		**0.010**	**0.008**	**.224**	**.629**
	Spatial Lag	**Log**		**0.009**	**0.008**	**.240**	**.811**
	Spatial Error	**Log**		**0.009**	**0.008**	**.278**	**.592**
Hypothesis 3: Designation as sundown county							
Implicit	**Linear Model**	**Raw**	.194	**0.013**	**0.004**	**.001**	**.089**
	Linear Model	**Log**	.285	**0.020**	**0.004**	**<.001**	**.179**
Explicit	Linear Model	Raw	.204	0.116	0.025	<.001	.001
	Linear Model	Log	.278	0.172	0.024	<.001	.001
	Spatial Lag	**Raw**		**0.092**	**0.043**	**.033**	**.824**
	Spatial Error	**Raw**		**0.086**	**0.046**	**.062**	**.622**
	Spatial Lag	**Log**		**0.125**	**0.044**	**.004**	**.842**
	Spatial Error	**Log**		**0.122**	**0.046**	**.008**	**.580**

Note. "Raw" refers to untransformed covariates, "Log" refers to log-transformed covariates. Bold indicates models without significant spatial autocorrelation.

Specification Curve Analyses

Our pre-registered analyses reflect specific theoretical choices about which covariates to consider, how to transform covariates, and whether to weight regions more strongly depending on the number of participants from that region. These pre-registered models mostly showed statistically significant effects (Table 1). To evaluate the robustness of our findings we conducted robustness checks and analysed our data without covariates (S1) and without weights (S2). These exploratory analyses mostly showed non-significant effects. To further evaluate the conditions under which these effects emerge, we conducted specification curve analysis (Simonsohn et al., 2020), using the specr package (version 1.00, Masur & Scharkow, 2020). We conducted one specification curve analysis for each of our three independent variables. For each specification curve, we included implicit bias and explicit bias dependent variables, unweighted regression analysis, weighted regression analysis, spatial lag, and spatial error models as statistical models, and the log-transformed versions of education, population density, proportion of Black people, and income as covariates. Each specification curve therefore included 128 unique specifications.

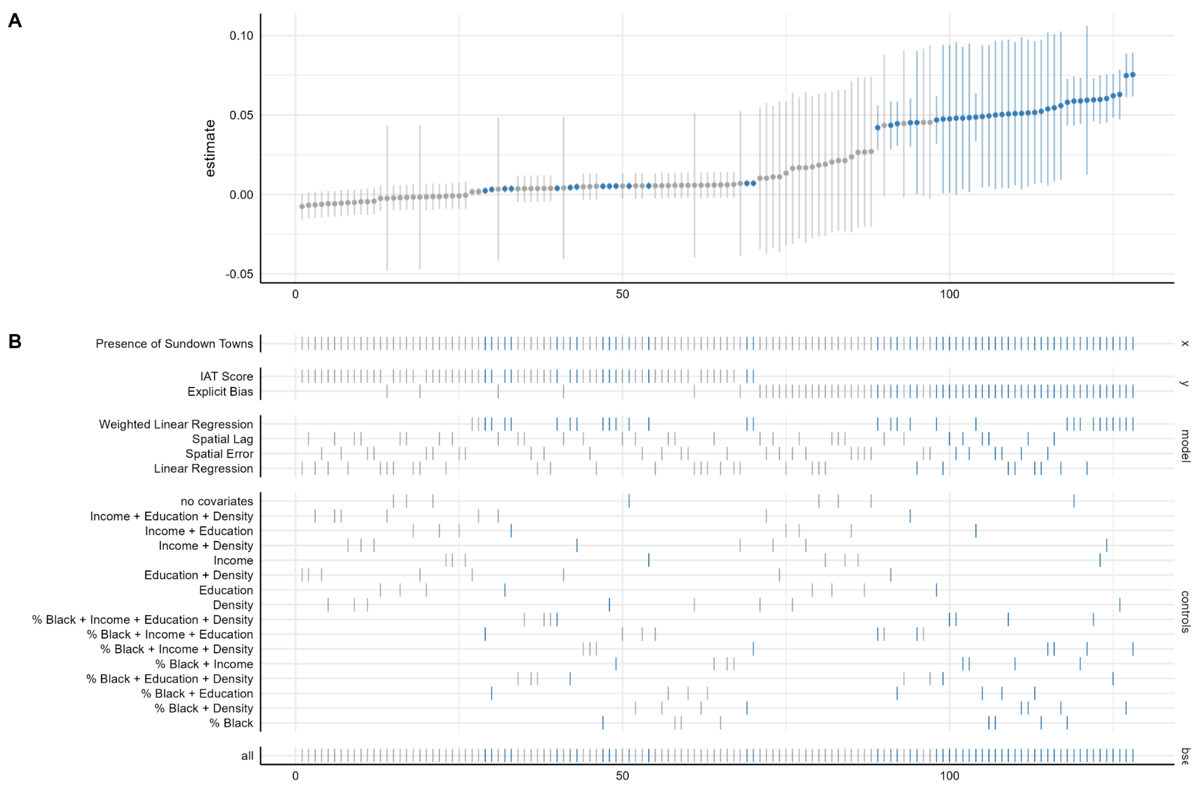

Figure 6. Specification curve analysis for presence of sundown towns in a county. Each point in the top graph represents an effect size for a different model specification and the vertical bars reflect the precision of that estimate. Effects illustrated in blue are significantly different from zero. Each vertical line in the bottom graph indicates the combination of covariates associated with each effect size.

For the presence of sundown tows in a county (Figure 6), the specification curve analysis reveals that the effect on implicit bias is present only for weighted regression models. Unweighted models and spatial regression models generally did not show significant effects on implicit bias. This finding is sensible because the main models predicting implicit bias did not show spatial autocorrelation (Table 1) so the spatial models should not be interpreted. For explicit bias, a wide range of model specifications is statistically significant, suggesting that the association between sundown towns and explicit bias is relatively more robust compared to the association with implicit bias. As models with explicit bias generally showed spatial autocorrelation, readers should only interpret the spatial regression models.

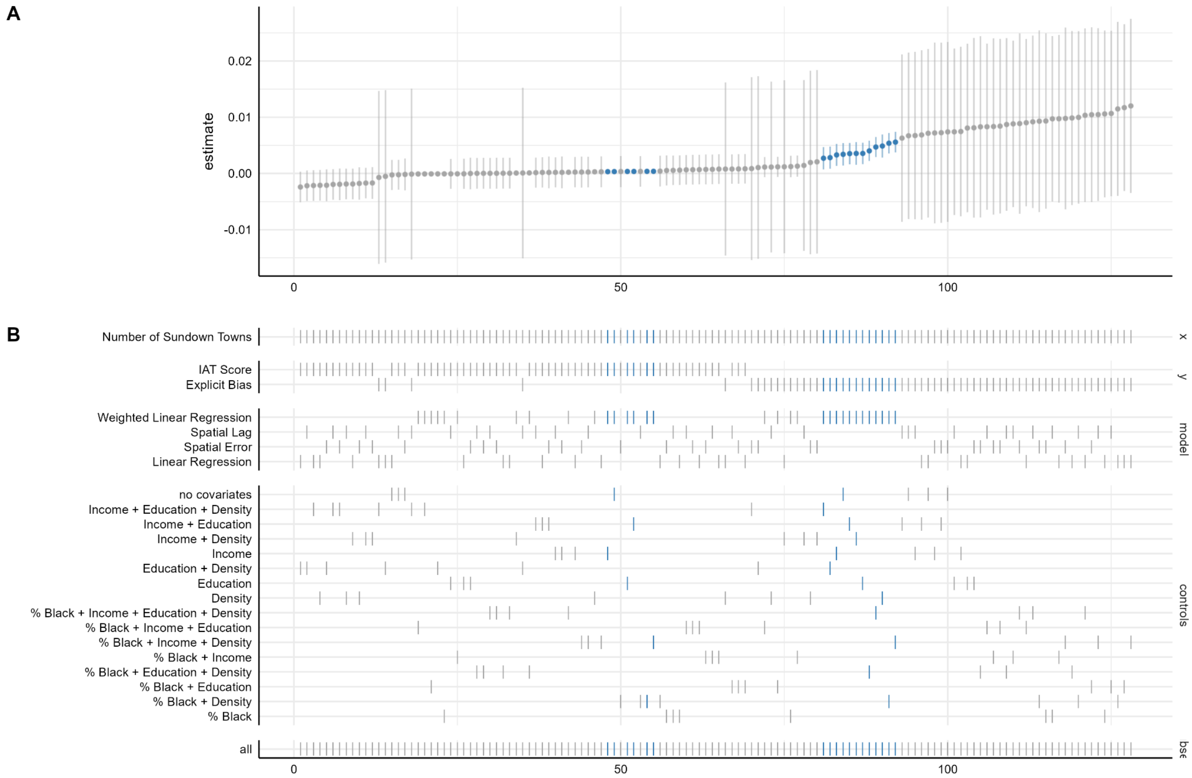

Figure 7. Specification Curve analysis for the number of sundown towns in a county. Each point in the top graph represents an effect size for a different model specification and the vertical bars reflect the precision of that estimate. Effects illustrated in blue are significantly different from zero. Each vertical line in the bottom graph indicates the combination of covariates associated with each effect size.

For the number of sundown towns in a county (Figure 7), the specification curve analysis shows significant results emerge only for weighted regressions with explicit bias as dependent variable. However, as models with explicit bias show spatial dependencies, the weighted regressions should not be interpreted. Therefore, the specification curve analysis provides additional support for our main (null) findings.

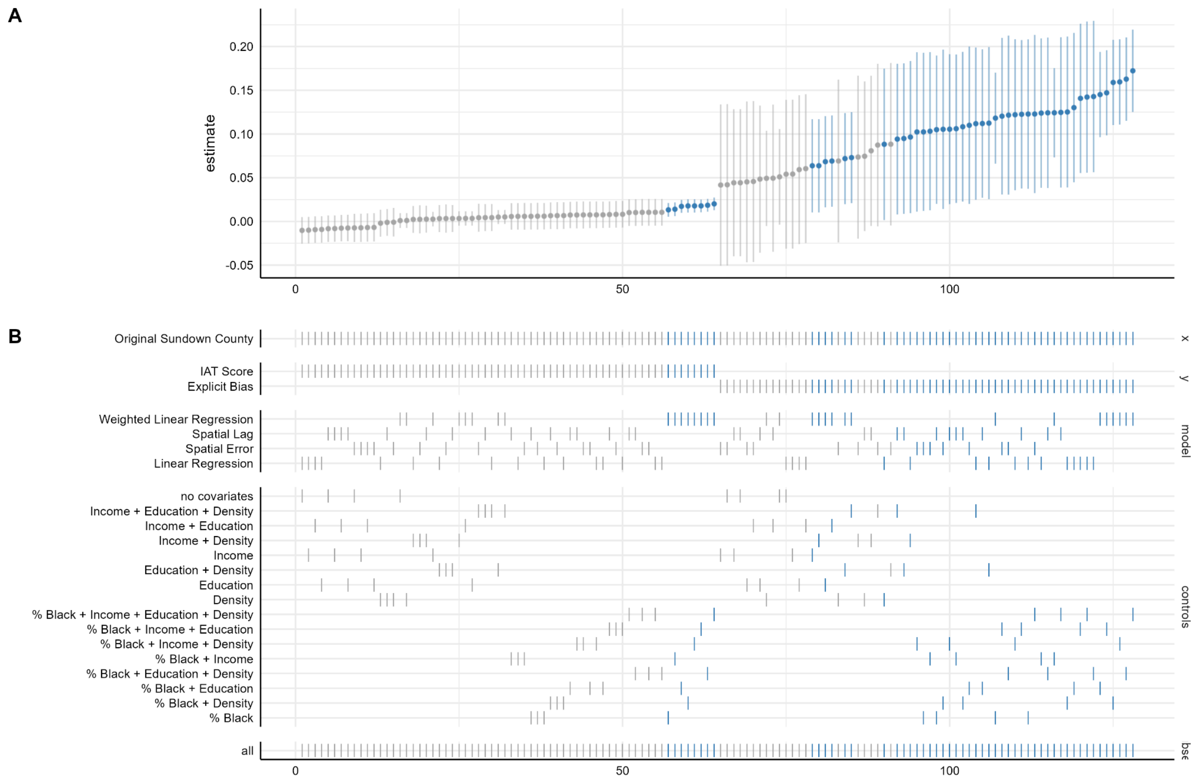

Figure 8. Specification curve analysis for Sundown counties. Each point in the top graph represents an effect size for a different model specification and the vertical bars reflect the precision of that estimate. Effects illustrated in blue are significantly different from zero. Each vertical line in the bottom graph indicates the combination of covariates associated with each effect size.

For counties designated as sundown (Figure 8), the specification curve analysis reveals that the effect on implicit bias is present only for weighted regression models. Because models with implicit bias showed no spatial dependencies, we again argue that readers should only interpret the weighted regression models. For explicit bias, many different model specifications emerge as significant, suggesting that the association between sundown counties and explicit bias is relatively more robust compared to the association with implicit bias. However, because models with explicit bias showed spatial dependencies, readers should only interpret the spatial regressions. In sum, the specification curve analyses provide important nuance to the results of the pre-registered analyses we report above. For explicit bias, they show that our findings are highly robust to alternative statistical decisions. For implicit bias, they show that our findings depend on the inclusion of regression weights.

Robustness Test: Inclusion Thresholds

Our primary analyses included all racial bias data from all available counties – even if county estimates reflected very few people and thus are relatively noisy or imprecise. Here, we repeated our analyses with counties that have at least 100 or 200 responses from Project Implicit volunteers, which increases the precision of county-level estimates. For these robustness checks we do not report or interpret the spatial regressions: removing counties with few observations leaves many counties without neighbours and thus makes the k-nearest neighbour weights we used in our spatial analyses inappropriate.

For both inclusion thresholds, the presence of a sundown town was associated with higher levels of implicit (H1a) and explicit racial bias (H1b), successfully replicating our main findings. Likewise, counties designated as sundown showed higher levels of implicit (H3a) and explicit (H3b) racial bias compared to other counties. We also replicated the null relationship between the number of sundown towns and implicit racial bias (H2a). However, in both threshold tests we found a significant association between the number of sundown towns and explicit racial bias (H2b) for log-transformed covariates only.

Taken together, these threshold tests largely replicate our main findings. That said, we caution against strongly interpreting them because all linear models showed spatial autocorrelation. Moreover, excluding counties with relatively few responses inadvertently removed almost all counties designated as sundown from the dataset: Out of 181 sundown counties, only 24 counties with at least 100 responses or 12 counties with at least 200 responses remained after we applied these inclusion thresholds. We present the full analytical results of these threshold tests in the supplementary materials (S3).

Replication: Skin Tone Bias

Sundown towns primarily aimed to restrict or exclude Black Americans. However, in practice, they often targeted racial or ethnic minorities more broadly. We therefore pre-registered and expected that the relationship between sundown towns and racial bias we observed in our main analyses would generalize to biases towards people with dark skin. We tested this prediction using data from the 2004 to 2024 subset of the Project Implicit Skin Tone dataset.

We summarize our findings here in the main text and report details in Table 2. Replicating our racial bias analyses, the presence of a sundown town was positively related to implicit skin tone bias. Also replicating our racial bias analyses, the number of sundown towns in a county was unrelated to implicit skin tone bias. However, diverging from our racial bias analyses, the presence of a sundown town was unrelated to explicit skin tone bias, and sundown county designation was unrelated to implicit and explicit skin tone bias. We therefore interpret these findings as offering mixed support for our prediction that the observed relationships between sundown towns and racial bias generalize to skin tone bias.

Table 2

Summary of Statistical Models: Skintone

Hypothesis	Analysis	Covariates	R^2	Coefficien	*SE*	*p*	*Moran's p*
Hypothesis 1: Presence of a sundown town in a county							

Implicit	**Linear Model**	**Raw**	**.209**	**0.006**	**0.001**	**<.001**	**.512**
	Linear Model	**Log**	**.222**	**0.005**	**0.001**	**<.001**	**.432**
Explicit	**Linear Model**	**Raw**	**.019**	**0.008**	**0.009**	**.370**	**.338**
	Linear Model	**Log**	**.023**	**0.009**	**0.009**	**.306**	**.319**
Hypothesis 2: Number of sundown towns per county							
Implicit	**Linear Model**	**Raw**	**.202**	**0**	**0**	**.170**	**.572**
	Linear Model	**Log**	**.218**	**0**	**0**	**.076**	**.426**
Explicit	**Linear Model**	**Raw**	**.019**	**-0.002**	**0.001**	**.121**	**.362**
	Linear Model	**Log**	**.023**	**-0.001**	**0.001**	**.224**	**.325**
Hypothesis 3: Designation as sundown county							
Implicit	**Linear Model**	**Raw**	**.202**	**0.001**	**0.004**	**.750**	**.572**
	Linear Model	**Log**	**.217**	**0.005**	**0.004**	**.196**	**.420**
Explicit	**Linear Model**	**Raw**	**.019**	**0.039**	**0.030**	**.197**	**.354**
	Linear Model	**Log**	**.024**	**0.055**	**0.030**	**.064**	**.342**

Note. “Raw” refers to untransformed covariates, “Log” refers to log-transformed covariates. Bold indicates models without significant spatial autocorrelation.

Discriminant Test: Age Bias

Though sundown towns discriminated against a wide variety of racial and ethnic minorities in the United States, their animus did not extend to other disadvantaged groups in society. Consequently, we predicted that the relationships we observed between sundown towns and racial biases should not extend to other groups. We tested this prediction using the 2002 to 2024 subset of the Project Implicit Age dataset. For this discriminant test, we pre-registered predictions of either null effects or attenuated effects compared to our main analyses that focus on racial bias.

We summarize our findings here in the main text and report details in Table 3. As predicted, we found null results for all analyses involving explicit bias, and for sundown counties and implicit bias. However, both the presence and number of sundown towns significantly and positively predicted implicit age bias. We therefore interpret these findings as offering mixed support for our prediction of null or attenuated relationships between sundown towns and intergroup bias in the context of age bias relative to racial bias.

Table 3

Summary of Statistical Models: Age

Hypothesis	Analysis	Covariates	R^2	Coefficient	*SE*	*p*	*Moran's p*
Hypothesis 1: Presence of a sundown town in a county							
Implicit	**Linear Model**	**Raw**	**.079**	**0.007**	**0.001**	**.006**	**.091**
	Linear Model	**Log**	**.102**	**0.005**	**0.001**	**.003**	**.072**
Explicit	Linear Model	Raw	.165	0.038	0.006	<.001	.001
	Linear Model	Log	.167	0.034	0.006	<.001	.001
	Spatial Lag	**Raw**		**-0.016**	**0.022**	**.478**	**.533**

	Spatial Error	**Raw**		**-0.017**	**0.022**	**.455**	**.521**
	Spatial Lag	**Log**		**-0.025**	**0.023**	**.267**	**.519**
	Spatial Error	**Log**		**-0.026**	**0.023**	**.253**	**.521**
Hypothesis 2: Number of sundown towns per county							
Implicit	**Linear Model**	**Raw**	**.068**	**0.001**	**0**	**<.001**	**.097**
	Linear Model	**Log**	**.095**	**0**	**0**	**.010**	**.108**
Explicit	Linear Model	Raw	.154	0.002	0.001	.045	.001
	Linear Model	Log	.158	0.001	0.001	.412	.001
	Spatial Lag	**Raw**		**0.005**	**0.007**	**.511**	**.537**
	Spatial Error	**Raw**		**0.005**	**0.008**	**.517**	**.521**
	Spatial Lag	**Log**		**0.003**	**0.008**	**.724**	**.524**
	Spatial Error	**Log**		**0.003**	**0.008**	**.733**	**.521**
Hypothesis 3: Designation as sundown county							
Implicit	**Linear Model**	**Raw**	**.061**	**-0.003**	**0.003**	**.308**	**.091**
	Linear Model	**Log**	**.093**	**-0.002**	**0.003**	**.633**	**.112**
Explicit	Linear Model	Raw	.154	0.025	0.020	.216	.001
	Linear Model	Log	.159	0.032	0.020	.107	.001
	Spatial Lag	**Raw**		**-0.001**	**0.041**	**.973**	**.537**
	Spatial Error	**Raw**		**-0.001**	**0.043**	**.985**	**.522**

Spatial Lag	**Log**		**0.003**	**0.042**	**.934**	**.523**
Spatial Error	**Log**		**0.005**	**0.043**	**.911**	**.521**

Note. "Raw" refers to untransformed covariates, "Log" refers to log-transformed covariates. Bold indicates models without significant spatial autocorrelation

Discriminant Test: Disability Bias

Further testing our prediction that sundown towns should not be related to other domains of intergroup bias, we conducted a second pre-registered discriminant test using the 2004-2024 subset of the Project Implicit Disability dataset.

We summarize our findings here in the main text and report details in Table 4. Sundown towns were positively and significantly related to disability bias in virtually all models, which speaks against our prediction of null effects. However, disability bias regression coefficients were descriptively smaller than corresponding racial bias regression coefficients for all analyses featuring explicit bias, and for sundown counties and implicit bias. Taken together, we interpret these findings as offering no support for our prediction of null effects, and mixed support for our prediction of attenuated relationships between sundown towns and intergroup bias in the context of disability bias relative to racial bias.

Table 4

Summary of Statistical Models: Disability

Hypothesis	Analysis	Covariates	R^2	Coefficient	*SE*	*p*	*Moran's p*

Hypothesis 1: Presence of a sundown town in a county							
Implicit	**Linear Model**	**Raw**	.164	**0.006**	**0.001**	**<.001**	**.673**
	Linear Model	**Log**	.159	**0.005**	**0.001**	**<.001**	**.618**
Explicit	**Linear Model**	**Raw**	.009	**0.011**	**0.006**	**.058**	**.452**
	Linear Model	**Log**	.017	**0.021**	**0.006**	**<.001**	**.458**
Hypothesis 2: Number of sundown towns per county							
Implicit	**Linear Model**	**Raw**	.162	**0.001**	**0**	**.003**	**.702**
	Linear Model	**Log**	.158	**0.001**	**0**	**.004**	**.598**
Explicit	**Linear Model**	**Raw**	.008	**0**	**0.001**	**.644**	**.432**
	Linear Model	**Log**	.014	**0.002**	**0.001**	**.046**	**.476**
Hypothesis 3: Designation as sundown county							
Implicit	**Linear Model**	**Raw**	.161	**0.011**	**0.005**	**.028**	**.698**
	Linear Model	**Log**	.157	**0.012**	**0.005**	**.014**	**.627**
Explicit	**Linear Model**	**Raw**	.011	**0.055**	**0.020**	**.007**	**.456**
	Linear Model	**Log**	.015	**0.052**	**0.020**	**.010**	**.498**

Note. “Raw” refers to untransformed covariates, “Log” refers to log-transformed covariates.

Bold indicates models without significant spatial autocorrelation

Sundown Towns versus Other Historical Inequalities

In subsequent exploratory models, we investigated whether sundown towns are associated with implicit and/or explicit racial bias above and beyond other historical inequalities that previous research has linked with regional racial bias. Modern racial bias is higher in regions of the United States characterized by greater numbers of enslaved people (Payne et al., 2019) and where more Black people resided during the Great Migration (Vuletich et al., 2024). Consequently, we repeated our main analyses with additional covariates reflecting the proportion of slaves in a county in 1860 (Payne et al., 2019) and the proportion of Black people in a county in 1930[3] (Vuletich et al., 2024).

We summarize our findings here in the main text and report details in Table 5. Replicating our main analyses, the presence of sundown towns was positively related to implicit (H1a) and explicit bias (H1b); sundown counties showed higher levels of implicit (H3a) and explicit (H3b) bias; and the number of sundown towns was not related to explicit bias (H2b). However, diverging from our main analyses, the number of sundown towns was positively related to implicit bias (H2a). Taken together, these analyses indicate that the relationship between sundown towns and regional racial biases cannot be explained by other historical inequalities.

Table 5

Summary of Statistical Models: Race, Slavery and the Great Migration

Hypothesis	Analysis	Covariates	R^2	Coefficient	*SE*	*p*	*Moran's p*
Hypothesis 1: Presence of a sundown town in a county							

[3] The relationship between racial bias and the proportion of Black people in a county during the Great Migration was largest in 1930 (Vuletich et al., 2024).

Implicit	**Linear Model**	**Raw**	**.287**	**0.009**	**0.001**	**<.001**	**.233**
	Linear Model	**Log**	**.331**	**0.007**	**0.001**	**<.001**	**.326**
Explicit	Linear Model	Raw	.271	0.079	0.008	<.001	.001
	Linear Model	Log	.308	0.079	0.008	<.001	.001
	Spatial Lag	**Raw**		**0.048**	**0.023**	**.035**	**.738**
	Spatial Error	**Raw**		**0.050**	**0.034**	**.046**	**.605**
	Spatial Lag	**Log**		**0.043**	**0.023**	**.059**	**.757**
	Spatial Error	**Log**		**0.044**	**0.024**	**.061**	**.573**
Hypothesis 2: Number of sundown towns per county							
Implicit	**Linear Model**	**Raw**	**.281**	**0.001**	**0**	**<.001**	**.208**
	Linear Model	**Log**	**.326**	**0.001**	**0**	**<.001**	**.241**
Explicit	Linear Model	Raw	.252	0.006	0.001	<.001	.001
	Linear Model	Log	.290	0.006	0.001	<.001	.001
	Spatial Lag	**Raw**		**0.012**	**0.007**	**.070**	**.746**
	Spatial Error	**Raw**		**0.013**	**0.007**	**.081**	**.604**
	Spatial Lag	**Log**		**0.007**	**0.007**	**.300**	**.759**
	Spatial Error	**Log**		**0.007**	**0.007**	**.326**	**.575**
Hypothesis 3: Designation as sundown county							
Implicit	**Linear Model**	**Raw**	**.275**	**0.014**	**0.004**	**<.001**	**.185**

	Linear Model	**Log**	**.327**	**0.020**	**0.004**	**<.001**	**.262**
Explicit	Linear Model	Raw	.248	0.121	0.027	<.001	.001
	Linear Model	Log	.291	0.176	0.027	<.001	.001
	Spatial Lag	**Raw**		**0.106**	**0.057**	**.062**	**.777**
	Spatial Error	**Raw**		**0.093**	**0.060**	**.120**	**.600**
	Spatial Lag	**Log**		**0.152**	**0.057**	**.008**	**.811**
	Spatial Error	**Log**		**0.144**	**0.059**	**.015**	**.560**

Note. "Raw" refers to untransformed covariates, "Log" refers to log-transformed covariates. Bold indicates models without significant spatial autocorrelation.

Discussion

Sundown towns reflect a shameful period in United States history, and the present research indicates that their legacy is not limited to the history books. Counties characterized in the past by either sundown policies or the presence of sundown towns have higher levels of racial bias today. These findings contribute to a growing body of research connecting historical inequalities with present-day intergroup biases, and more broadly support situational models of bias linking prejudices with environments.

The present research represents an important theoretical contribution to our understanding of the relationship between environments and biases, in part, because it is high in statistical validity – and we can calibrate our confidence in empirical findings to the extent that they are statistically valid. The present research is characterized by very large sample sizes, multiple measures of the focal construct (implicit and explicit bias), and results that are robust across a variety of analytic choices and operationalizations of the research question.

That said, we were surprised that one of those operationalizations – the number of sundown towns per county – did not predict present-day racial biases. This apparent null result could reflect limitations of the data that we did not anticipate in advance: Most counties contained either 0 or 1 sundown towns, and very few counties included high numbers of both sundown towns and Project Implicit participants (see Figure 4). Thus, restricted range and/or lack of data may obscure the predicted relationship between the number of sundown towns per county and racial biases. Furthermore, we want to note that the observed effect sizes are very small. That is, the difference on the IAT D-Score between counties that contained sundown towns and counties that did not is 0.005. Nevertheless, we argue that these differences are important because the social and cultural environments created by sundown towns potentially shape people's behaviours (see Anvari et al., 2023; Götz et al., 2022 and Primbs et al., 2023 for a conversation on interpreting small effect sizes). For example, Black people are substantially less likely to visit public parks that are within former sundown towns compared to parks that are not in former sundown towns (Rigby et al., 2026).

Moreover, our tests of the generalizability and discriminant validity did not come out entirely as predicted. The discriminant tests, in particular, are intended to shore up an anecdotal criticism of regional psychology studies, namely, that large sample sizes make them statistically "overpowered" and biased towards significant findings. Given that the relationship between sundown counties and racial bias (H3) did not generalize to skin tone bias, we have demonstrated that the present research is not biased towards significant findings. With that said, the skin tone IAT specifically might be limited by methodological issues that we did not initially appreciate. The skin tone IAT relies on differently-coloured sketches of people as stimuli instead of real human faces like the race IAT uses. These sketches might not be realistic enough to activate race-related biases. In line with this argument, Project Implicit recently updated the skin tone IAT to include real faces rather than sketches. Once Project Implicit accumulates sufficient data from this updated skin tone IAT, future research should follow-up on the present study to assess whether the effects we found using the race IAT replicate with a skin tone IAT that uses stimuli that are higher in ecological validity.

Moreover, generalizability and discriminant tests are necessarily guided by theory, and in interpreting some of our unexpected findings we cannot rule out the possibility that our theory was wrong. The pattern of results that emerged across the present research indicates that sundown towns are more weakly related to skin tone bias, but more strongly related to age and especially disability bias, than we expected. A robust literature on generalized intergroup bias (Adorno et al., 1950; Allport, 1954; Hodson & Dhont, 2015; Hodson & Puffer, 2025) finds that people who are prejudiced against some outgroups are often also prejudiced towards other outgroups. This phenomenon could potentially explain the relationships between sundown towns and age and disability bias. However, theory related to generalized intergroup bias – and psychological theories in general – is articulated on the person-level, whereas the present research was conducted at the regional level. Our findings suggest that generalized intergroup bias could also exist at the regional level. Sundowns towns expressly discriminated against Black people, and in doing so potentially fostered social and cultural environments that perpetuate bias against other stigmatized groups. Consequently, the present research lays a foundation for future research to investigate how and why biases co-occur within geographical regions.

Despite its strengths, the present research is limited in three main ways. First, Project Implicit is an opt-in sample that is not representative of the United States population. Most sundown towns are in rural counties, and we are not aware of a representative dataset that contains sufficient measures of intergroup bias to replicate our analyses. However, past research using Project Implicit data has replicated their findings in representative samples (e.g., Ofosu et al., 2019; Primbs et al., 2024b), and regional demographics of the Project Implicit sample correlate very strongly with data from the US Census (Hehman et al., 2018).

Second, given that all of the variables in the present research were measured rather than manipulated, we are unable to make strong causal claims with these data. Psychological theory clearly predicts a causal relationship between historical inequalities and modern racial bias (Payne & Hannay, 2021), and temporal precedence rules out the reverse causal pathway. Nevertheless, many possible confounding variables and alternative causal pathways may produce the observed effect. Moreover, the link between sundown towns and racial bias may well be recursive: The presence of strong local racial biases likely contributed to the emergence of sundown towns. In turn, administrative and cultural forces within sundown towns likely perpetuated racial biases over time. Historical inequalities may therefore be a product of past biases, and at the same time the cause of present-day biases.

Third, the present research cannot make claims about the mechanism(s) linking sundown towns with modern-day biases. Payne and colleagues (2019) argued that communities that were more dependent on slavery developed norms, laws, and institutions that justified slavery and resisted racial equality. Though our analyses show that sundown towns are associated with racial biases above and beyond slavery and other inequalities, they may be viewed as a more recent iteration of this same White supremacy that employed similar processes to sustain their ideologies. Both formal (e.g., laws, ordinances) and informal (e.g., biased policing, norms) aspects of sundown towns may have contributed to the persistence of biased attitudes over time: Sundown towns offered limited opportunities for positive intergroup contact; discriminatory policies and policing may have signaled biased social norms; and frequent violence would have contributed to dehumanization of Black people. Future research might use agent-based modeling (e.g., Smaldino et al., 2015) or transmission chain experiments (e.g., Mesoudi & Whiten, 2008) to investigate how and why bias transmits across generations.

Civil rights reforms largely put an end to the formal institutions of sundown towns in the United States. However, the present research demonstrates that discriminatory beliefs do not end when discriminatory practices are outlawed. Instead, the legacy of prejudiced and exclusionary practices persists over decades, and is still evident in the minds of people today. Though we can and should celebrate legislative victories for justice and equality, our findings illustrate the importance of continuing those efforts even after a particular discriminatory practice is outlawed.

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