PNAS

Historical roots of implicit bias in slavery

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Edited by Jennifer A. Richeson, Yale University, New Haven, CT, and approved April 23, 2019 (received for review November 4, 2018)

Implicit racial bias remains widespread, even among individuals who explicitly reject prejudice. One reason for the persistence of implicit bias may be that it is maintained through structural and historical inequalities that change slowly. We investigated the historical persistence of implicit bias by comparing modern implicit bias with the proportion of the population enslaved in those counties in 1860. Counties and states more dependent on slavery before the Civil War displayed higher levels of pro-White implicit bias today among White residents and less pro-White bias among Black residents. These associations remained significant after controlling for explicit bias. The association between slave populations and implicit bias was partially explained by measures of structural inequalities. Our results support an interpretation of implicit bias as the cognitive residue of past and present structural inequalities.

implicit bias | slavery | bias of crowds | prejudice

As the Civil War loomed, Abraham Lincoln acquired a map drawn using new cartographic methods. It depicted the proportion of the population enslaved in each county based on the 1860 Census. With the help of his map, the president correctly predicted that states most dependent on slave labor would be the most committed to secession, whereas border states with fewer slaves could be persuaded to remain in the Union (1). Slavery shaped not only the secession of states, but also the institutions, economies, and cultures that followed for generations. In this article, we use the data from Lincoln's map to investigate the legacy of slavery in terms of contemporary implicit racial biases. We find that residents of counties more dependent on slave labor in 1860 display greater implicit bias measured up to 156 y later.

Implicit bias refers to mental associations triggered automatically on thinking about social groups (2–4). The expression of implicit bias is difficult to conceal or manipulate because it is measured using performance on cognitive tests, not based on self-report. In contrast, explicit attitudes are voluntarily self-reported based on introspection. Survey research suggests that explicitly reported prejudice has declined across decades (5), whereas implicit bias remains prevalent (6–8). This divergence may reflect changing social norms against overtly expressing prejudice. Neither type of bias appears to exclusively track "true" attitudes; rather, implicit bias and explicit bias are often independently associated with discriminatory behavior (9–12).

Implicit bias has been invoked to explain continued disparities across the fields of social sciences, natural sciences, and law (13–16). However, despite its scholarly influence, implicit bias research has been controversial. Meta-analytic summaries suggest that associations between a person's implicit bias score and behavioral measures of discrimination are small but statistically significant (7, 17, 18). Measures of implicit bias have been criticized on psychometric grounds (19), such as low temporal stability (average test-retest $r = 0.41$ over a 2- to 4-wk period; ref. 20).

Criticisms of implicit bias research assume that implicit bias is a feature of the person, akin to beliefs or personality traits. From this individual difference perspective, low temporal stability and small individual difference correlations are troubling. An alternative perspective, however, argues that implicit bias is not primarily a trait of individuals but rather a feature of social contexts (21). According to this view, implicit bias reflects largely transient activation of associations cued by stereotypes and inequalities in social environments. For any individual, activated biases may be idiosyncratic and ephemeral; however, implicit bias operates like the "wisdom of crowds" phenomenon, in which independently assessed knowledge, when aggregated, tends to be more accurate than the partial knowledge of any individual (22, 23). Similarly, aggregate levels of implicit bias may reflect the stability of inequalities in the local environment, even though associations for each individual are fleeting and noisy. We describe this model as the "bias of crowds" because the same processes that give rise to the wisdom of crowds can give rise to systematic biases when those processes operate in contexts with preexisting inequalities (21).

This context-based perspective is consistent with theorizing across the social sciences that has emphasized the ways in which social and cultural contexts shape individual cognition. For example, Lamont et al. (24) have argued that although some cognitive processes involved in implicit bias are universal, such as semantic associations and the use of schemas, the content and meaning of those cognitions are shaped by cultural repertoires and scripts. Those cultural repertoires and scripts, in turn, vary geographically and across social networks and are themselves shaped by historical processes (24). Based on this reasoning, they urged better integration between research on implicit bias and the study of cultural processes that transmit inequality. Shepherd (25) elaborated on the connection between laboratory research showing malleability in implicit bias and sociological approaches to culture. Given that physical context, media, and cultural symbols have all been shown to alter implicit biases, Shepherd argued that these effects should not be viewed as merely perturbations of scores around a person's baseline. Instead, the responsivity of implicit bias to the social environment can be

Significance

Geographic variation in implicit bias is associated with multiple racial disparities in life outcomes. We investigated the historical roots of geographical differences in implicit bias by comparing average levels of implicit bias with the number of slaves in those areas in 1860. Counties and states more dependent on slavery in 1860 displayed higher pro-White implicit bias today among White residents and less pro-White bias among Black residents. Mediation analyses suggest that historical oppression may be transmitted into contemporary biases through structural inequalities, including disparities in poverty and upward mobility. Given the importance of contextual factors, efforts to reduce unintended discrimination might focus on modifying social environments that cue implicit biases in the minds of individuals.

Author contributions: B.K.P., H.A.V., and J.L.B.-I. analyzed data and wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1818816116/-/DCSupplemental.

Published online May 28, 2019.

interpreted as a cognitive reflection of racialized associations in the culture.

Our bias of crowds model attempts to bridge the intraperson focus common in psychology with research on the structural and cultural forces that perpetuate inequality. Consistent with this social context perspective, aggregate measures of implicit bias, such as national, state, and county-level averages, are robustly associated with such outcomes as racial disparities in health (26), infant health (27), police shootings (28), and gender disparities in STEM fields (29). These aggregate-level associations are generally stronger than individual difference associations (21).

If aggregate-level implicit bias is a valid reflection of structural racism, then we may be able to detect the enduring structural legacy of slavery in today's implicit bias. Communities that were dependent on slave labor developed laws, institutions, ideologies, and informal norms to justify the practice of slavery in the antebellum South and to resist racial equality following emancipation (30, 31). Following the Civil War, southern states passed "Black Codes," laws that limited property rights and freedom of movement and that allowed Black citizens to be impressed into forced labor for even minor infractions. After the US Congress intervened to overturn the Black Codes in 1868, most southern states passed a new set of "Jim Crow" laws by the 1890s restricting freedoms for Black citizens. These laws, which explicitly restricted voting and officially segregated housing, schools, and public facilities, remained in effect until the Civil Rights Act of 1964 and the Voting Rights Act of 1965. Although not codified by law, segregation enacted by banks, zoning practices, and other institutions was common in the northern states as well (32). Since the Civil Rights era, laws and practices that are race-neutral on their face continue to disadvantage Black citizens, including drug laws and voter identification laws (33, 34).

The historical legacy of discrimination has created structural inequalities that may continue to cue stereotypical associations long after official legal barriers have been removed. Because areas with larger enslaved populations in 1860 had more reason to justify slavery and resist equality, we hypothesized these areas would have higher levels of implicit bias today. To test the association between enslaved populations and implicit bias, we merged data from the 1860 census and data on implicit racial bias measured using the Implicit Association Test (IAT). The race IAT measures the speed with which respondents can associate racial categories "Black" and "White" with pleasant and unpleasant words. The IAT provides a relative measure of association strength. Higher scores reflect more positive associations to Whites relative to Blacks, whereas negative scores reflect more positive associations to Blacks than Whites.

The bias of crowds model argues that implicit biases are cued by structural inequalities in the contemporary environment, but it does not specify what those cues are. Research on the cultural transmission of inequality has identified several distinct pathways that may serve this cuing function. Most concretely, the transmission of material resources tends to preserve inequalities across generations (35). To measure the effects of material resources, we used data on racial disparities in poverty in each county. A second pathway runs through ecological influences, such as residential segregation and neighborhood effects, which transmit inequalities through physical and social environments (36, 37). To measure ecological influences, we used data on racial segregation by county. Finally, researchers have noted that inequalities are also transmitted through many less tangible but nonetheless important processes, including social capital, cultural assumptions (24), shared cognitive schemas and frames (38), and selective knowledge and ignorance of history (39). These pathways are difficult to measure directly. We measured racial disparities in intergenerational economic mobility to estimate the cumulative effect of observable and unobservable influences that function to maintain social hierarchies over time. By integrating these data sources, we tested the hypothesis that areas with larger enslaved populations before the Civil War have higher levels of implicit bias today, and that structural inequalities may link historical oppression to modern bias.

Results

Associations Between Slave Populations and Implicit Bias. A graphical representation of the data is provided in Fig. 1, which displays the proportion of the population of each county enslaved in 1860 (*Left*), mean IAT scores for White residents (*Middle*), and mean IAT scores for Black residents (*Right*). Consistent with our hypothesis, counties and states with a higher proportion of their populations enslaved in 1860 had greater anti-Black implicit bias among White residents. The bivariate correlation was $r(1{,}441) = 0.37$ ($P < 0.0001$) at the county level and $r(40) = 0.64$ ($P < 0.0001$) at the state level (Fig. 2).

To account for the nested structure of the data, we investigated these associations using multilevel modeling procedures. All models controlled for county population and land area. Dependent variables were *z*-scored so that differences could be interpreted in SD units. For White residents, the proportion of slaves in 1860 predicted current levels of implicit bias at both county and state levels (*SI Appendix*, Table S1, model 1). For counties, a change in the proportion of the population

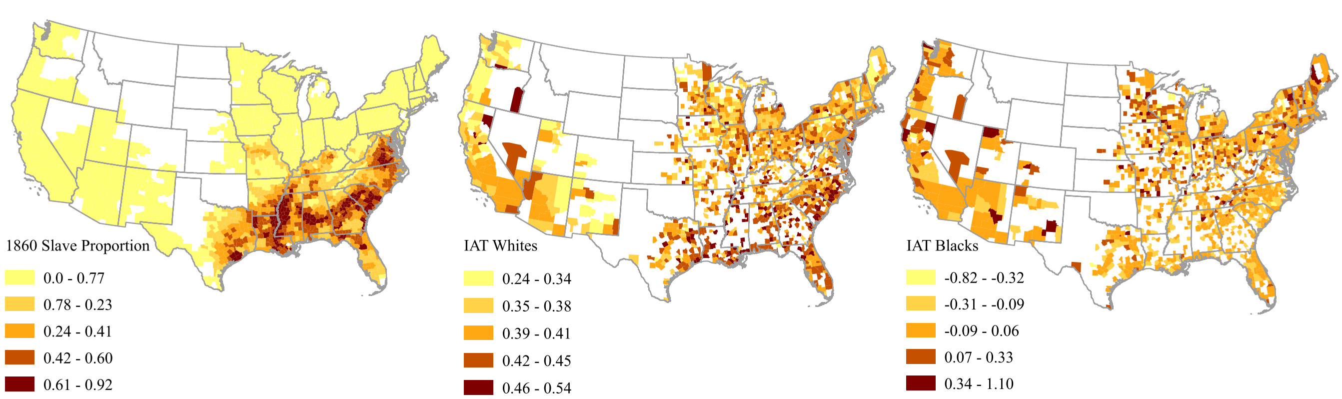

Fig. 1. Maps displaying slavery and implicit bias trends. (*Left*) Proportion of each county's population enslaved in 1860. (*Middle*) Average implicit bias among White respondents. (*Right*) Average implicit bias among Black respondents. Legend colors are scaled within each race group for the purpose of visualization. IAT scores for Whites are positive for all counties, reflecting pro-White bias. Scores for Blacks range from strongly pro-White (positive values) to strongly pro-Black bias (negative values). Areas in white have no data.

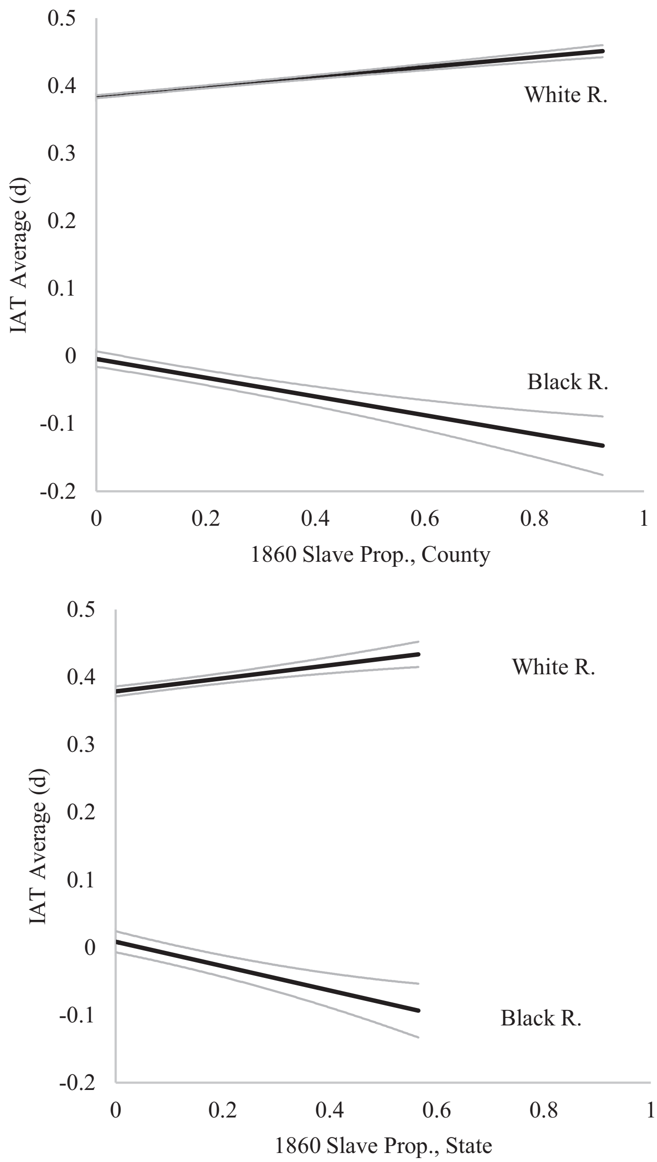

Fig. 2. Bivariate associations between slavery proportions in 1860 and IAT averages at the county (*Top*) and state (*Bottom*) levels. Higher IAT average denotes greater pro-White bias. Gray lines denote 95% CIs. Prop., proportion; R., respondents.

enslaved from 0 to 1 was associated with a 1 SD increase in implicit bias ($b = 1.0$, $P < 0.001$). At the county level, the SD for IAT scores was 0.04. This effect size is equivalent to the difference between San Francisco County, California (0.33) and Fayette County, Kentucky (home of Lexington; 0.37). At the state level, the change was >2 SDs ($b = 2.06$, $P < 0.001$). With a state-level SD of 0.03, this is equivalent to the difference between Washington state (0.35) and North Carolina (0.41). The association between slave populations and implicit bias remained significant when controlling for explicit bias (40) for both counties ($b = 0.84$, $P < 0.001$) and states ($b = 1.24$, $P < 0.001$).

Black residents displayed a distinctive pattern. Black respondents had much lower bias and greater variability than White respondents (Fig. 2). In contrast to the results for White residents, larger enslaved populations were associated with more negative associations to Whites relative to Blacks at both the county level [$r(1{,}368) = -0.16$, $P < 0.001$] and state level [$r(40) = -0.59$, $P < 0.001$]. These results were robust when accounting for the nested structure of the data using multilevel models. After controlling for county population and land area, the proportion enslaved was associated with less implicit bias at the county level ($b = -0.81$, $P < 0.001$) and the state level ($b = -0.72$, $P < 0.001$) (*SI Appendix*, Table S2, model 1). The association remained significant when controlling for explicit bias for counties ($b = -0.66$, $P < 0.01$) but not for states ($b = -0.38$, $P = 0.07$). These associations suggest that larger enslaved populations are associated with greater bias favoring the in-group over the out-group.

Population Diversity and Historical Slavery. We next investigated an alternative hypothesis that the association observed may be driven by the proportion of Black residents currently living in the region rather than by the proportion historically enslaved. Previous research has found that implicit bias among Whites is higher in states with larger Black populations (41). In the years following the Civil War, Black populations were nearly identical to formerly enslaved populations, in part because Black residents were often not allowed to move freely. But population demographics gradually changed throughout the twentieth century, reflecting what became known as "the great migration." Large numbers of Black residents moved, often from rural southern areas into northern cities. We estimated a series of multilevel models entering the 1860 slave population in each county simultaneously with the proportion of the population that was Black for each census decade. (Not all decades had population data by race available.) We examined whether slave populations or current Black populations in each decade uniquely predicted implicit race bias.

The coefficients reported in Table 1 for White and Black respondents are regression coefficients from a series of models that predicted IAT scores from both the 1860 slave population and the Black population proportion from one census year. As seen in the table, the correlation between the proportion of slaves in 1860 and proportion of Black residents in early decades (1870–1940) was very high, ranging from 0.90 to 0.96.* In the early decades, the unique associations for slave populations and Black populations were inconsistent for both White and Black respondents, likely reflecting the very high degree of multicollinearity. In the later decades, when slave populations and Black populations became more statistically distinguishable, the patterns stabilized. For White respondents, implicit bias was associated with slave populations but not with modern Black populations. For Black respondents, in contrast, implicit bias was associated with contemporary Black populations but not with slave populations.

These unique effects should be interpreted with caution due to multicollinearity across all years; nonetheless, the pattern suggests another interesting dissociation in the potential sources of implicit bias among Whites and Blacks. Whereas historical inequalities continue to shape the biases of Whites, implicit biases among Black respondents may be cued more by contemporary demographics.†

Specificity of Race Bias. Our hypothesis assumes that the history of slavery set the conditions not just for any kind of bias, but specifically for racial bias. We tested the specificity of this link by comparing race bias to measures of weight and gender bias. The weight IAT measured positive associations for thin people

*We did not examine the population associations at the state level because the correlations between slave populations and Black populations were extremely high in all years, ranging from 0.93 to 0.99.

†We also examined whether the association between implicit bias and slave populations depended on the present-day proportion of the population that is Black, and found that the interaction between slave proportion and (log-transformed) Black population in 2010 was not significant for White respondents ($P = 0.45$) or Black respondents ($P = 0.37$).

Table 1. Implicit bias simultaneously regressed on slave population in 1860 and Black population in each census year

Census year	Correlation between slave population and Black population	White respondents		Black respondents	
		1860 slave population	Black population	1860 slave proportion	Black population
1870	0.92	0.83*	0.14	−0.78*	0.03
1880	0.96	0.57	0.39	−0.57	−0.28
1900	0.94	0.70	0.37	−0.60	−0.27
1910	0.91	0.83*	0.19	−0.68	−0.16
1920	0.90	0.42	0.74*	−0.54	−0.39
1930	0.91	0.46	0.73*	−0.54	−0.38
1940	0.90	0.47	0.74*	−0.64	−0.34
1970	0.87	0.75**	0.53	−0.29	−1.07**
1980	0.84	0.84**	0.36	−0.33	−1.09**
1990	0.82	0.86***	0.34	−0.39	−1.01**
2000	0.80	0.87***	0.32	−0.44	−0.91**
2010	0.79	0.87***	0.32	−0.47	−0.83*

The second column shows the correlation between the two population estimates for each year. *$P < 05$; **$P < 01$; ***$P < 001$.

relative to overweight people, and the gender IAT measured associations between gender and family vs. career categories. We estimated multilevel models to test the county- and state-level associations with slave populations for each. Slave populations were not associated with implicit weight bias among White respondents at the county level ($b = 0.22$, $P = 0.594$) or the state level ($b = 0.24$, $P = 0.383$). Likewise, slave populations were unrelated to implicit weight bias among Black respondents at either the county level ($b = 0.29$, $P = 0.483$) or the state level ($b = 0.15$, $P = 0.601$).

Gender bias was marginally associated with slave populations among Whites at the county level ($b = -0.33$, $P = 0.054$) but not the state level ($b = 0.10$, $P = 0.501$). The negative coefficient at the county level indicates that larger slave populations were, unexpectedly, associated with less traditional gender stereotypes. Among Black respondents, slave populations were not related to gender bias at the county level ($b = 0.11$, $P = 0.601$), but were associated with more traditional gender stereotypes at the state level ($b = 0.65$, $P < 0.001$). Thus, gender bias had an inconsistent relationship with slave populations. However, when controlling for gender and weight bias in a multilevel model, the association between slave populations and racial bias remained robust for both White and Black respondents and at both the county and state levels (*SI Appendix*, Tables S3 and S4, model 3). These findings suggest that the history of slavery is associated robustly and specifically with implicit race bias.

Potential Pathways Linking Slavery to Implicit Bias. Finally, we investigated structural inequalities as potential mediators of the association between slavery and implicit bias. Although these analyses are necessarily exploratory, we drew on sociology research on the cultural transmission of inequality and on the bias of crowds model of implicit bias to select three potential mediating variables. We examined the proportion of people in poverty who are Black and the proportion who are White, intergenerational mobility among White and Black residents, and residential segregation. We used measures describing White and Black residents separately as independent predictors because our hypothesis was that structural inequalities affecting the status of Black residents, but not of White residents, cue stereotypic associations.

The data for these measures came from several sources (*Materials and Methods*). As displayed in Table 2, each structural inequality measure was significantly associated with slave populations at both the county level (above the diagonal) and the state level (below the diagonal). The structural inequality measures also tended to be intercorrelated with one another. This general pattern of associations provides initial evidence that structural inequalities may link slavery to implicit bias.

To examine the mediating role of each variable individually, we estimated indirect effects in a multilevel model with simultaneous mediators. Table 3 presents the unique indirect effects of each variable. Because these variables are correlated with the demographics of the population, we included the proportion of Black residents based on the 2010 US Census as a covariate. Among White respondents, the county-level association between slave populations and implicit bias was mediated by the proportion of the poor in each county who are Black ($b = 0.11$, $P = 0.012$). The

Table 2. Correlations among structural inequality measures, slave populations, and implicit bias at the county level (above the diagonal) and the state level (below the diagonal)

Variable	1	2	3	4	5	6	7	8
1. Slavery 1860	—	0.37***	−0.16***	−0.56***	0.79***	−0.26***	−0.25***	0.44***
2. IAT White	0.64***	—	−0.05	−0.18***	0.36***	−0.17***	−0.24***	0.21***
3. IAT Black	−0.59***	−0.65***	—	0.14***	−0.18***	0.06*	0.15***	−0.15***
4. Poverty White	−0.47**	−0.38*	0.29	—	−0.74***	−0.06**	0.09***	−0.81***
5. Poverty Black	0.90***	0.78***	−0.65***	−0.58***	—	−0.17***	−0.26***	0.63***
6. Mobility White	−0.42**	−0.36*	0.27	0.07	−0.36*	—	0.55***	0.02
7. Mobility Black	−0.47**	−0.64***	0.44**	0.20	−0.49***	0.55***	—	−0.09***
8. Segregation	0.50***	0.49**	−0.33*	−0.94***	0.63***	−0.13	−0.34*	—

*$P < 0.05$; **$P < 0.01$; ***$P < 0.001$.

Table 3. Indirect effects of proportion of enslaved population on implicit bias among White and Black IAT respondents (separate models) through structural inequality mediators

	White respondents				Black respondents			
	Indirect effect, county level		Indirect effect, state level		Indirect effect, county level		Indirect effect, state level	
Mediator	*b*	*P*	*b*	*P*	*b*	*P*	*b*	*P*
Poverty White	0.01	0.442	−0.06	0.876	0.01	0.474	0.03	0.877
Poverty Black	0.11	0.012	−0.09	0.691	0.02	0.688	−0.01	0.810
Mobility White	0.01	0.397	−0.45	0.240	0.002	0.860	0.18	0.547
Mobility Black	0.05	0.042	0.18	0.682	−0.10	0.009	−0.06	0.708
Segregation	−0.02	0.805	0.02	0.964	0.13	0.094	−0.01	0.964

All mediators were entered simultaneously. All models controlled for proportion of Black residents based on the 2010 census, county population, and land area at both the county and state levels.

slavery-bias association was also mediated by lower mobility among Black residents ($b = 0.05$, $P = 0.042$). No other measures exhibited unique indirect effects. These indirect effects suggest that racial disparities in poverty and in economic mobility may partially account for the long-term transmission of inequality from slavery to present-day implicit bias.

Among Black respondents, the sole unique indirect effect was intergenerational mobility for Blacks at the county level ($b = -0.10$, $P = 0.009$). Larger enslaved populations were associated with less upward mobility, and less upward mobility was associated with diminished implicit biases favoring Blacks over Whites.

These correlational data cannot identify causal relationships. The temporal precedence of slavery suggests that it likely contributed to the inequalities and biases that followed. However, the associations between structural inequalities and implicit bias may each influence the other, as structural inequalities cue biased thoughts, which may in turn lead to greater inequalities. These mediation results merely indicate that there is sufficient shared variance that structural inequalities could play the theoretically predicted mediating role.

Discussion

Our results shed light on the importance of history to modern forms of prejudice. Two hundred and forty-six years passed between the arrival of the first slave ship in the American colonies and the abolition of slavery in 1865. Another century and a half later, slavery's legacy remains perceptible. Counties and states more dependent on slavery in 1860 now have greater implicit bias among Whites, suggesting that intergroup stereotypes and attitudes are more likely to be automatically triggered in those areas.

These effects were observed at both state and county levels, although state effects were consistently larger. There may be at least two reasons for the larger state-level effects. First, state effects include aggregation across larger numbers, which results in estimates that are more precise with less error. Second, most of the laws that maintained structural inequalities, beginning with slave laws and extending to Black Codes, Jim Crow laws, and so on, were passed at the state level. However, in addition to these state-level effects, the county level effects suggest that less formal but more proximal experiences also play a role in cueing implicit bias.

The implicit biases of Black and White residents were in many ways mirror images of each other. The legacy of slavery was associated with greater pro-White biases among Whites but with pro-Black biases among Blacks. The same inequalities that cue stereotypes in the mind of White respondents may cue discrimination in the minds of Black residents. This person–context interaction is consistent with a standard social psychological analysis emphasizing the social environment as it is construed by the individual.

A limitation of this study is that the IAT data are not representative of the US population (sample and US demographic data are compared in *Materials and Methods*). Most significantly, our IAT sample was younger, more racially diverse, and more highly educated than the US population. Nonrepresentative sampling is a limitation for all Project Implicit data; nonetheless, this source is currently the sole archive of implicit bias data large enough for drawing conclusions at the county and state levels.

The concept of implicit bias has been influential because it may help explain the persistence of discrimination even when individuals reject explicitly prejudiced attitudes (2–4). This dissociation suggests that implicit forms of prejudice may persist even when explicit prejudice recedes. The findings reported here suggest even greater permanence at the aggregate level than was previously appreciated. Conceptually, these findings support a theory of implicit bias that emphasizes the social environment (21). Implicit bias is a distinctly modern conception of prejudice, but it has historical roots that dramatically shift its interpretation. Rather than solely a feature of individual minds, implicit bias may be better understood as a cognitive manifestation of historical and structural inequalities (42). Practically speaking, these results suggest that in efforts to remediate implicit bias, more attention should be given to modifying social environments as opposed to changing the attitudes of individuals.

Materials and Methods

Data Sources. To test our main hypothesis, we merged two datasets. The first dataset came from the 1860 US Census, as aggregated in previous research (40) and downloaded from *The Journal of Politics* dataverse (43). We examined the proportion of the total population in each county who were enslaved based on the 1860 Census (the data source for Lincoln's map and the last counting of enslaved populations before the Civil War). The proportion of slaves ranged from 0 to 92%.

To measure implicit racial bias, we used data from Project Implicit, which has collected information from millions of users based on the IAT (44). This test measures the association between racial categories "Black" and "White" and evaluations of "good" and "bad." The metric is an effect size measure, in which 0 reflects no difference in the speed of classifying the racial categories with good versus bad evaluations. Higher values on this measure reflect a greater implicit bias in favor of Whites over Blacks, whereas negative values reflect a bias in favor of Blacks over Whites. To achieve stable county-level measures of implicit bias, we averaged the IAT scores across White respondents in all counties that had at least 100 observations, resulting in a dataset of 1,443 counties for analyses of White residents and 1,370 counties for analyses of Black residents. Counties that were excluded due to insufficient observations had nearly identical IAT scores as counties that were retained (mean ± SD, 0.39 ± 0.13 vs. 0.39 ± 0.04). Our final dataset, which was restricted to the counties with slavery data available and only included responses from White and Black residents, included more than 2.5 million respondents from Project Implicit collected between 2002 and 2016. Our final sample was 58.9% female, 58.8% White, and 10.6% Black or African American, with a median age of 23 y and 34.7% with a bachelor's degree or higher. The general population, according to the 2010 US Census, is 50.8% female, 72.4% White, and 12.6% Black or African American, with a median age of 37.5 y and 27.3% of adults age >18 y with a bachelor's degree or higher.

The Project Implicit data included ratings of feelings toward Whites and Blacks to measure explicit racial attitudes (the same as one of the measures used in previous research; ref. 40). We used the difference between these ratings to measure explicit bias; higher values reflect more positive feelings for Whites than for Blacks.

To test the specificity of the correlation between slavery and racial bias, we used Project Implicit datasets on weight bias (2004–2017) and gender-career bias (2005–2017). These IATs probed associations between the concepts of "good/bad" and "thin/overweight" for weight bias and "male/female" and "family/career" for gender-career bias. Higher scores on the weight IAT indicate positive associations between good and thin, and high scores on the gender-career IAT indicate positive associations between male and career. As with race bias, we aggregated responses for counties with 100 or more observations, resulting in 2,283 counties for gender-career bias and 613 counties for weight bias.

Our measures of structural inequalities came from several sources. We downloaded data on overall, White, and Black total population in poverty from the American Community Survey, using 2012–2016 5-y estimates. From these estimates, we then calculated the proportion of people in poverty who are Black and the proportion who are White. Data on commuting-zone level absolute economic mobility were publicly available at Opportunity Insights (https://opportunityinsights.org/data/) and were published previously (45). These data were compiled from federal tax returns between 1996 and 2012. Absolute mobility was coded as the mean household income rank within each commuting zone for an adult child with parents in the 25th percentile of the national income distribution. We converted commuting zone estimates to county estimates using census equivalencies.

Finally, our measure of residential segregation came from the 1990 and 2000 US Census, as compiled in the RTI Spatial Impact Factor Database. Original scores were calculated such that higher numbers indicated a greater probability of Blacks and Whites meeting (lower segregation). We reverse-scored this variable so that higher numbers can be interpreted as indicating greater residential segregation.

Analytic Approach. To account for the nested structure of the data (counties: level 1; nested within states: level 2), we used multilevel modeling procedures with restricted maximum likelihood estimation. We predicted county-level IAT scores from the proportion of slaves in each county nested within each state. We allowed for random intercepts at the level of the state (level 2). To isolate within-state effects, all predictor variables were state mean-centered. Our main outcome variable, county-level IAT scores, was standardized. Thus, multilevel modeling coefficients can be interpreted as the SD change in implicit bias associated with a 1-unit increase in a predictor while holding all other variables at their mean for that state.

All models controlled for log-transformed county area (in miles) and log-transformed county population (based on the 2010 census) at levels 1 and 2, to account for the population density of counties and the mean population density of counties within states.

We ran two models to investigate whether the proportion of slaves in each county in 1860 would predict current implicit bias. Based on previous theory and inspection of the current data, each model was run separately for White and Black participants, for a total of four models. Level 1 and level 2 model equations and all model coefficient estimates are provided in *SI Appendix*. Models testing for the specificity of the correlation between slavery and racial biases as well as models accounting for the proportion of Black residents in each census decade followed a similar format as our main models. The equations in *SI Appendix* apply to them, with the addition of the corresponding independent variables at level 1 and state averages at level 2. For all models, only intercepts included random effects.

Finally, for our mediation analysis, all structural inequality variables were entered simultaneously at level 1. The proportion of Black residents according to the 2010 US Census, log-transformed land area, and log-transformed population size were included as covariates in all legs of the model. All analyses were performed with SAS 9.4.

ACKNOWLEDGMENTS. We thank Lee R. Mobley for making data available from the RTI Spatial Impact Factor Database. This work was funded in part by National Science Foundation Grant 1729446 (to B.K.P.) and by a National Science Foundation Graduate Fellowship and a Paul and Daisy Soros Fellowship for New Americans (to H.A.V.).

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