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The Great Migration and Implicit Bias in the Northern United States

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Abstract

The spatial patterning of present-day racial bias in Southern states is predicted by the prevalence of slavery in 1860 and the structural inequalities that followed. Here we extend the investigation of the historical roots of implicit bias to areas outside the South by tracing the Great Migration of Black southerners to Northern and Western states. We found that the proportion of Black residents in each county (N = 1,981 counties) during the years of the Great Migration (1900–1950) was significantly associated with greater implicit bias among White residents today. The association was statistically explained by measures of structural inequalities. Results parallel the pattern seen in Southern states but reflect population changes that occurred decades later as cities reacted to larger Black populations. These findings suggest that implicit biases reflect structural inequalities and the historical conditions that produced them.

Keywords

implicit bias, the Great Migration, structural inequality, IAT, regional differences

During the First World War, Black Americans began leaving Southern farms for Northern and Western cities. States north and west offered manufacturing jobs that paid higher wages than farming and offered an escape from the Jim Crow system of racial subjugation. Between 1910 and 1970, nearly six million Black Americans left. This mass exodus, which became known as the Great Migration, was the largest internal relocation in U.S. history, dwarfing the 19th-century gold rush and the 20th-century dust bowl migration combined (Tolnay, 2003; Wilkerson, 2010).

The Great Migration transformed Northern and Western cities. Historians argue that the concentration of Black Americans in these cities contributed, for example, to the Harlem Renaissance and the development of the Civil Rights Movement (Arnesen, 2003). Simultaneously, White backlash to larger Black populations led to new structural barriers for Black Americans in the North and West. White authorities responded to the growing Black populations by segregating neighborhoods and schools (Massey & Denton, 1993; Rothstein, 2017). For example, restrictive covenants kept Black families in Black-only areas of cities. Federal housing policies known as redlining prevented Black residents from obtaining mortgages, limiting their ability to build wealth. Black workers were barred in many places from joining labor unions and were relegated to low-wage work. Black Americans seeking to escape Jim Crow segregation in the South found the system partially rebuilt around them in Northern and Western cities.

In this article, we examined the legacy of the Great Migration for present-day racial biases. We hypothesized that counties with larger populations of Black residents during the first half of the 20th century would show greater implicit bias among White residents today. We also predicted that this association would be partly explained by the level of systemic racism in those counties. Our aim was to show that, unlike the Southern United States, where regional implicit bias can be traced to slavery and Jim Crow systems, in the North and West, the roots of implicit bias for White Americans can be traced to the Great Migration.

Theoretical Framework: How Historical Racism Relates to Inequality and Implicit Bias

Implicit bias describes mental links between social groups and evaluations or stereotypes (Banaji, 2001; Fazio & Olson, 2003; Petty et al., 2008). It is measured using

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performance on cognitive tests, rather than self-report, making it more difficult to conceal or manipulate than explicit attitudes. Explicit attitudes, in contrast, are self-reported using traditional survey methods. Although both explicit and implicit bias have been declining over time, race bias on implicit measures remains more prevalent than in explicit reports (Charlesworth & Banaji, 2019; Schuman et al., 1997). The literature on implicit bias does not treat either type of bias as the "true" attitude; rather, implicit and explicit bias are often independently associated with discriminatory behavior (Amodio & Devine, 2006; Dovidio et al., 2002; Kurdi et al., 2019). Because of these independent effects, implicit bias has often been invoked to explain continued discrimination even among people who do not explicitly endorse prejudiced attitudes.

Research suggests that features of social environments can cue implicit bias. Although the biases activated in specific individuals can be transient, aggregated measures of bias in a city, county, or state reflect the collective biases in that context and are more enduring. As many aspects of environments remain stable over time, aggregate implicit bias can be highly stable (Payne et al., 2019; Vuletich & Payne, 2019). Several kinds of environmental features have been found to correlate with average levels of implicit bias. Racial biases among White Americans are higher, for example, in metro areas with poorer health and fewer health care providers (Hehman et al., 2021), and in states with lower Medicaid spending (Leitner et al., 2018). Implicit bias is higher on college campuses with fewer Black faculty, lower upward mobility among students, and more confederate monuments (Vuletich & Payne, 2019). Aggregate scores are also associated, in some cases quite strongly, with racial disparities in important outcomes. For example, county-, city-, or state-level biases are associated with racial disparities in health (Leitner et al., 2016; Orchard & Price, 2017), education (Chin et al., 2020), school discipline (Riddle & Sinclair, 2019), and police use of force (Hehman et al., 2018).

These associations raise questions about the origins of context-based implicit biases, and why some places are more racially biased than others. Some research suggests that aggregate implicit biases may track long-term structural features. For example, variability in implicit gender biases across cultures tracks stereotypes embedded in languages (Charlesworth et al., 2021; Lewis & Lupyan, 2020). Most relevant to the present research, the proportion of the population enslaved in each county in 1860 was associated with greater implicit racial bias among White residents today (Payne et al., 2019). That association was partially statistically explained by markers of systemic racism, including modern-day racial segregation and racial disparities in poverty and upward mobility. Areas more dependent on slavery in the antebellum South erected more structural barriers for Black Americans following the Civil War, which can still be detected today in patterns of segregation and economic disparities. Those present-day racial disparities, in turn, may cue biased associations in the minds of people who inhabit those spaces. Payne and colleagues (2019) suggested that large racial inequalities cue racial stereotypes in the minds of White residents, leading to higher levels of implicit preferences for White over Black individuals. These findings suggest that structural inequalities rooted in slavery and its aftermath may contribute to implicit bias and maintain it more strongly in some places than others.

Those findings primarily reflected variability in Southern states, where enslavement was widespread in 1860. However, implicit and explicit bias obviously exist outside of the South. In the present research, we focused on Northern and Western states following the Civil War. We examined U.S. Census estimates of the Black populations in each county in each decade to test whether—and when—the differential proportions of Black populations throughout the Great Migration became predictive of higher levels of implicit race bias today.

We hypothesized that, just as in the South, areas with larger Black populations would have higher levels of systemic inequalities (indexed by the proportion of Black residents among the poor, lack of economic mobility for Black residents, and residential segregation), and these systemic inequalities would in turn be associated with modern racial bias for White residents. However, we expected the relevant time frames to be later in the North and West, following the path of the Great Migration. We did not have a basis to predict which years during the Great Migration would be most relevant for contemporary implicit bias. Hence, we examined the link between implicit bias and Black populations for each census decade during that period (1910–1970). For comparison, we also examined the link between implicit bias and Black populations before and after the Great Migration (1870–1900 and 1980–2010). We did not expect population characteristics during those periods to be as strongly linked to implicit bias as the intervening years. In addition, we examined associations with explicit bias as a point of comparison. As we mentioned previously, although explicit and implicit bias tend to be positively correlated, they also show independent associations with other variables. Because explicit bias can be modulated to conform to local norms, self-presentation concerns, and other factors, we did not have an a priori hypothesis for this variable about the pattern of associations to population characteristics before, during, and after the Great Migration.

In exploratory analyses, we also examined implicit biases among Black residents and their relation to Black populations across the decades. Previous work has shown that Black residents show stronger implicit biases in favor of Black over White people in places where there is more structural inequality and a history of greater dependence on slavery (Payne et al., 2019). We expected our findings to be consistent with this previous work and reveal that larger Black populations (and greater structural inequality) are

Table 1. *Descriptive Statistics and Zero-Order Correlation Matrix for the Focal Variables*

Variable	Year of measurement	Descriptive statistics *M*	*SD*	Zero-order correlations (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Implicit bias (White respondents)	2002–2018	0.37	0.03	1.00							
(2) Explicit bias (White respondents)	2002–2018	0.58	0.21	.76***	1.00						
(3) Past proportion of Black residents	1930	0.03	0.05	.16***	.05*	1.00					
(4) Total population count	2010	1,022,027	1,680,172	−.12***	−.24***	.05*	1.00				
(5) County area	2010	1,254	2,147	−.10***	−.14***	−.15***	.30***	1.00			
(6) Present proportion of Black residents	2010	0.09	0.10	.07**	−.05*	.60***	.22***	−.17***	1.00		
(7) Proportion of people living in poverty who are Black	2010	0.16	0.15	.13***	.05*	.58***	.18***	−.22***	.93***	1.00	
(8) Intergenerational mobility among Black residents	1980–2012	34.01	3.19	−.23***	−.26***	−.14***	−.09***	.03	−.20***	−.30***	1.00
(9) Racial residential segregation	2010	29.02	21.38	.38***	.32***	.48***	.14***	−.30***	.66***	.69***	−.40***

Note. We used weights to account variations in the number of participants from one county to another.
$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$.

associated with a stronger bias among Black respondents favoring Black over White people. However, we did not have an a priori hypothesis about the pattern of associations across census decades.

Method

Sample

The implicit and explicit racial bias data used in this study came from the Project Implicit (https://implicit.harvard.edu/implicit/), an organization that collects data through a demonstration site visited by millions of users every year. We used county-level racial bias averages and only included counties: (1) in states[1] outside the confederacy (54% of the Implicit Association Test [IAT] data set), and (2) with nonmissing values (90% of the data set). These inclusion criteria yielded 37 states with 1,981 counties for White respondents (representing 1,636,473 IAT respondents) and 1,361 counties for Black respondents (representing 214,875 IAT respondents).

Variables

Table 1 presents the descriptive statistics and zero-order correlations for White respondents (full correlation tables for White and Black respondents are in the Supplementary Information).

Implicit and Explicit Bias (County-Level Averages)

Implicit Bias From 2002 to 2018 (Main Outcome). Visitors to the Project Implicit demonstration website take an IAT that measures people's associations between the racial categories "Black" and "White" and evaluations "Good" and "Bad" (Xu et al., 2014). Higher scores mean greater pro-White/anti-Black bias. Scores correspond to an effect size and range from negative to positive, with values of 0 reflecting no difference in the speed of categorizing racial categories with good/bad ratings. We averaged responses for all years from 2002 to 2018 at the county level for White and Black respondents separately.

Explicit Bias From 2002 to 2018 (Additional Outcome). Visitors to the Project Implicit website also respond to questions about their racial attitudes. We used two "thermometer" scales to construct our measure of explicit bias. These items asked respondents to rate how warmly they feel toward White and Black people on a scale of 0 (*very cold*) to 10 (*very warm*). We subtracted warm feelings toward Black people from warm feelings toward White people to calculate an explicit bias score and averaged responses for all years from 2002 to 2018 at the county level for White and Black respondents separately.

Structural Variables (County-Level Sociodemographics)

Proportion of Black Residents From 1870 to 2010 (Focal Predictor). Population data for each census year from 1870 to 2010, came from IPUMS-NHGIS (Manson et al., 2022). Higher values indicate greater proportions of Black residents among the total population in the county for each year. We also collected three potential population confounders: county area, total population count, and Black population in census year 2010. We used them as control variables when testing the effects of the past proportion of Black residents in the regression analysis. Because the distributions of the population variables were right-skewed, we log-transformed all values.

Proportion of People Living in Poverty Who Are Black, 2008–2012 (Intervening Variable 1). Poverty data came from the American Community Survey "Table S1701, 5-year estimates (2008–2012)," disaggregated by county and race (U.S. Census Bureau, 2012). For our analyses, we used the proportion of individuals below the poverty line who are Black.

Intergenerational Economic Mobility Among Black Residents from 1980 to 2012 (Intervening Variable 2). Economic mobility data came from Opportunity Insights and included commuting zone income rank statistics for Black children born between 1980 and 1991 of parents in the bottom 25th percentile of income level (Chetty et al., 2014).[2] Higher values on this measure indicated more economic mobility (children who have moved up the income ranks in 1996–2012 in reference to their parents in 1980–1991).

Racial Residential Segregation in 2010 (Intervening Variable 3). Residential segregation data came from the American Communities Project (n.d.) and were based on the 2010 decennial census. We used an isolation index that measures, at the level of metropolitan areas, Black residents' exposure to other Black residents. Values ranged from 0 to 100, with higher values indicating greater residential segregation. For instance, a value of 56.3 means that the average Black resident in a given metropolitan area lives in a neighborhood that is 56.3% Black.

Data Availability. Although the data used here are publicly available through the source sites, the merged data file, a codebook, and the scripts to reproduce the analysis are available on the OSF page of the project: https://osf.io/b8m9e/.

Results

Analysis Plan

Our first question was whether past proportions of Black residents in Northern and Western counties (using populations estimates from 1870 to 2010) are associated with modern-day implicit bias (using aggregated implicit bias data from 2002 to 2018). We used a bivariate correlation analysis and applied analytical weights to account for the fact that some counties had fewer participants and thus less accurate estimates of the aggregated bias, while other counties had more participants and thus more accurate estimates of the aggregated bias (Dupraz, 2013). We first report the correlations among White respondents, and then among Black respondents.

Next, we built a regression model with standard errors (*SE*s) adjusted for state clustering (accounting for the non-independence of residuals within states). In this model, we used past population characteristics (from the period of the Great Migration) to predict implicit bias while statistically controlling for the proportion of Black residents in 2010. We also controlled for county area and total county population to address the possibility of selective migration to larger, more urban, and densely populated counties, which might have different levels of implicit bias compared with smaller, more rural, and less densely populated areas. As in the correlational analysis, we used weights to account for variations in the number of participants from one county to another.

Next, we performed a *specification curve analysis* as a robustness check, an analytical tool that enabled us to test all reasonable regression models testing the association between past proportion of Black residents and current implicit bias (Simonsohn et al., 2020). This analysis accounts for the fact that we made methodological and analytical decisions to construct what we think is the most reasonable model. However, some of these decisions can be arbitrary in nature (e.g., operationalizing the past proportion of Black residents using data from one year rather than another), and different researchers might have chosen to build a different model (for an empirical illustration, see Silberzahn et al., 2018). The following features were allowed to vary across models: the specific census year used to predict implicit bias, variable transformations, inclusion of control variables, and the method for accounting for unequal county number of responses (more details in the sections below).

Finally, we aimed to test the hypothesis that communities responded to how large the Black population was during the Great Migration by creating enduring systemic inequalities that continue to cue biases in modern-day county residents. Specifically, we tested the mediational role of systemic inequalities using the same three variables that were found, in the South, to mediate the association between enslaved populations and implicit bias: (1) proportion of people living in poverty who are Black, (2) intergenerational economic mobility among Black residents, (3) racial residential segregation (Payne et al., 2019). Each intervening variable was matched, as closely as possible, to the period covered by the implicit bias data. We used a structural equation model (SEM) with SEs adjusted for state clustering. Our model tested whether the relation

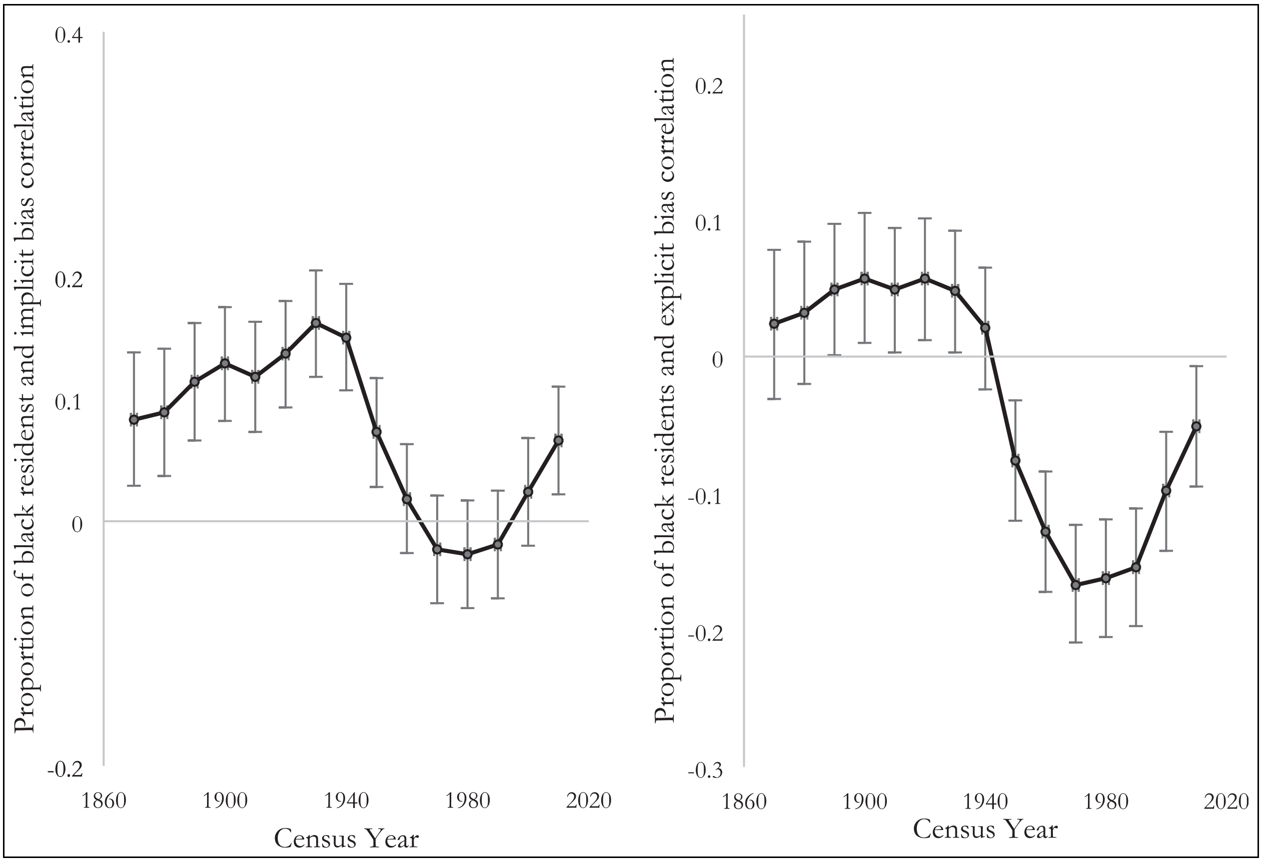

Figure 1. *Associations Between Percent Black Population in Each Census Year and White Residents' Implicit and Explicit Racial Bias Scores*
Note. The left panel shows positive correlations between county-level proportions of Black residents for each census year and county-level pro-White/anti-Black implicit bias among White respondents today. The correlation peaks in 1930, a couple of decades into the Great Migration, and is not significant for the years 1960–2000. The right panel shows positive (for the years 1860–1940) and negative (for the years 1950–2010) correlations between county-level proportions of White residents for each census year and county-level pro-White/anti-Black explicit bias among White respondents today. Error bars indicate 95% confidence intervals.

between past proportion of Black residents and current implicit bias operated through a latent variable labeled "structural inequality," which was based on these three components. We included the same control variables used in the regression analysis and we again used weights to account for the variations in the number of participants from one county to another.

Correlational Analyses

Implicit and Explicit Bias Among White Respondents. First, we tested the bivariate correlations between the proportion of Black residents in each county for each census year and measures of implicit bias among White residents today (with analytic weights). As seen in Figure 1 (left panel), the county-level proportion of Black residents across the years was positively associated with implicit bias favoring White over Black individuals today. Specifically, the association peaked in 1930, $r = .16$, 95% confidence interval (CI) = [0.12, 0.20], $p < .001$, and it was not significant in the years 1960 through 2000 (after the Great Migration). These results are consistent with our hypothesis that population characteristics during the years of the Great Migration relate more strongly to implicit bias today compared with years outside this period. Note that the Black population size in 2010 was correlated with implicit bias, which is accounted for by the fact that the implicit bias data span from 2002 to 2018, capturing the societal context of 2010.

We used the same procedure to test the correlations between the proportion of Black residents in each county for each census year and measures of *explicit* bias among White residents today. As seen in Figure 1 (right panel), explicit bias followed a very different pattern: Correlations were positive or null for years 1860 through 1940, and after 1940, counties with larger proportions of Black residents showed *less* explicit bias among White residents. An asymptotic chi-square test for the equality of two correlation matrices revealed that the matrix pertaining to implicit bias was significantly different from the matrix pertaining to explicit bias, $\chi^2(120) = 5{,}088$, $p < .001$. The dissociation between implicit and explicit bias as a function of Black populations is interesting because implicit and explicit bias

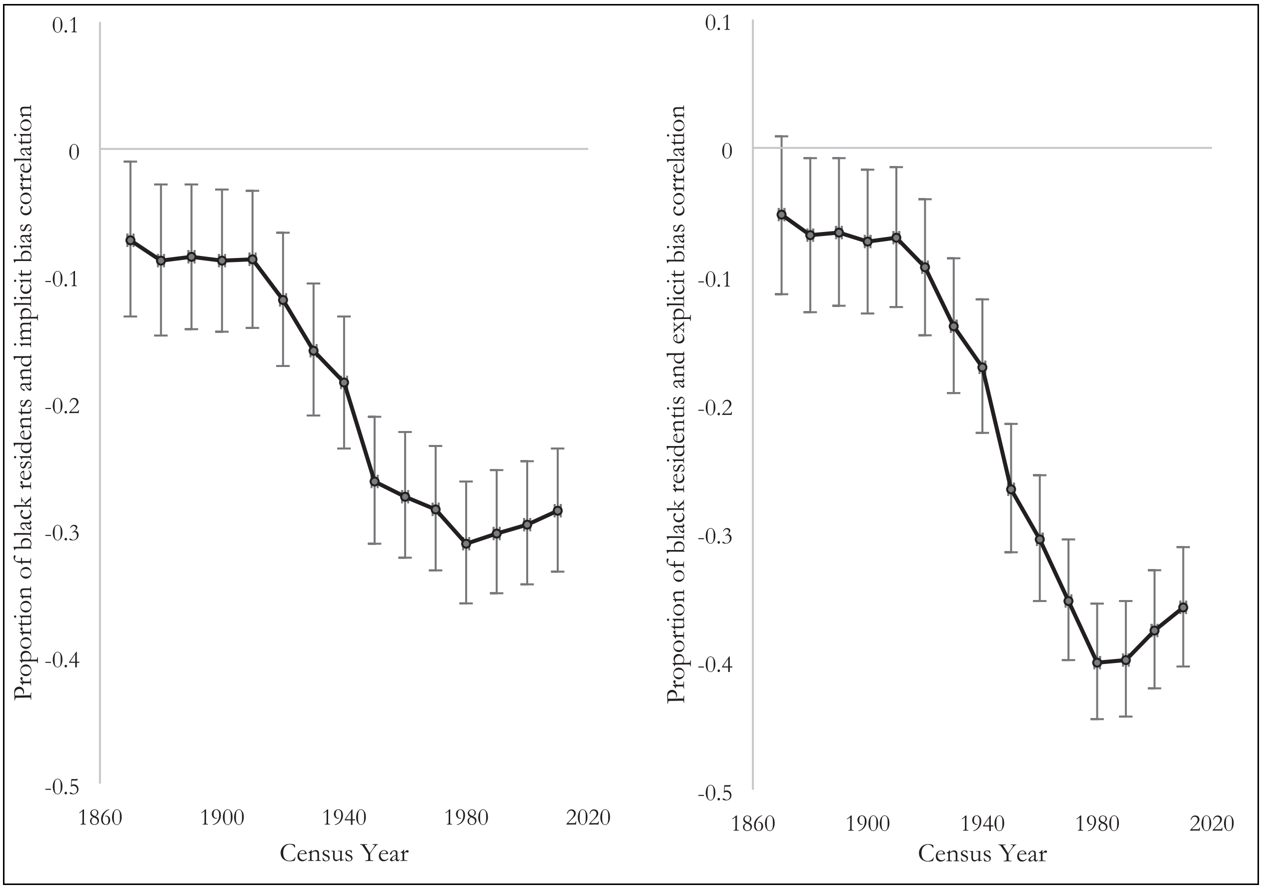

Figure 2. *Associations Between Percent Black Population in each Census Year and Black Residents' Implicit and Explicit Racial Bias Scores*
Note. The left panel shows negative correlations between county-level proportions of Black residents for each census year and county-level pro-White/anti-Black implicit bias among Black respondents today. Greater proportions of Black residents are associated with less pro-White bias (or more pro-Black bias) among Black respondents, and this relation is stronger when considering more recent population counts. The right panel shows a similar negative correlation with pro-White/anti-Black explicit bias that is stronger when considering more recent population counts. Error bars indicate 95% confidence intervals.

are positively correlated across counties and tend to correlate with other variables in the same direction (Hehman et al., 2019).

Implicit and Explicit Bias Among Black Respondents. We used the same procedure described above to test the bivariate correlations between the proportion of Black residents in each county for each census year and measures of implicit bias among Black residents today. The pattern of findings was different from the pattern observed with White residents. As seen in Figure 2 (left panel), counties with larger proportions of Black residents displayed greater pro-Black implicit bias among Black residents, and this association was stronger when considering more recent population counts. Unlike the implicit biases of White respondents, the implicit biases of Black respondents appeared to be more strongly tied to contemporaneous demographic characteristics rather than past population characteristics. It is worth noting that, even though the link to past population characteristics was not as strong as the link to contemporaneous characteristics, the implicit biases of Black residents were still tied to structural inequalities, $r = .20$. (Black mobility), $r = -.31$ (proportion of the poor who are Black), and $r = -.29$ (residential segregation) (full correlation table in the Supplemental Information). The correlations suggest that higher levels of structural inequality in an area are associated with greater pro-Black (or anti-White) implicit bias among Black residents.

We again used the same procedure to test the bivariate correlations between the proportion of Black residents in each county for each census year and measures of *explicit* bias among Black residents today. As seen in Figure 2, this pattern of larger modern Black populations being associated with more pro-Black evaluations was consistent across implicit and explicit measures for Black respondents (the two correlation matrices were not different from one another, $\chi^2(120) = 50.88$, $p = 1.00$), and it mirrored the pattern observed for White residents' explicit bias. The implicit biases of White residents were unique in both the direction

Table 2. *White Respondents' Implicit Bias Predicted by Black Populations in 1930*

Predictor	β	SE^a	p	95% CI
Proportion of Black population in 1930	0.11	0.04	.016	[0.02, 0.20]
Proportion of Black population in 2010	0.07	0.03	.051	[0, 0.13]
County area in 2010	0.02	0.03	.508	[−0.03, 0.07]
Total county population 2010	−0.15	0.03	<.001	[−0.20, −0.09]

Note. We used weights to account for variations in the number of participants from one county to another. Because the distribution of population variables is right-skewed, all predictors were log-transformed. All variables were standardized. CI = confidence interval.
[a]Cluster-adjusted (number of state clusters = 37).

of the association (positive) and the timing of the populations that mattered (decades within the Great Migration).

Regression Analyses

Next, we accounted for the nesting of counties within states and separated the effect of past population characteristics from the effect of current population characteristics. All variables were standardized for ease of interpretation. Below is the cluster-adjusted weighted regression equation (which accounts for nonindependent residuals within states):

$$\sqrt{n_j} \cdot \overline{IAT}_j = \beta_0 + \sqrt{n_j} \cdot \beta_1 \cdot \log\left(\overline{Black\ Prop_j}\right) + \sqrt{n_j} \cdot \beta_k \cdot \log\left(\overline{Control}_{k_j}\right) + \sqrt{n_j} \cdot \bar{\mu}_j$$

. . . where $j = 1, 2, \ldots N$ [counties], $\sqrt{n_j}$ represents analytic weights (with n being the number of respondents per county), $\overline{IAT}_j$ represents the standardized county-aggregated implicit bias score, $\overline{BlackProp_j}$ represents the standardized proportion of Black residents in 1930, and $\overline{Control}_{k_j}$ represents a vector of the three standardized population control variables in 2010, and μ is the error term.

Table 2 presents the full findings. The association between the county-level proportion of Black residents in 1930 and implicit bias observed in the correlational analyses remained significant, $\beta = 0.11$, 95% CI = [0.02, 0.20], $p = .016$. Importantly, the proportion of Black population in 1930 explained variance *over and above* the proportion of Black population in 2010, as well as county area and total county population in 2010.

Robustness Check

As a robustness check, we conducted a specification curve analysis using the following four specification dimensions: (1) census year of measurement of past proportion of Black residents (ranging from 1900 to 1950, that is, the significant correlations for the Great Migration–related census years observed in the preliminary correlational analysis), (2) procedure accounting for the between-county variation in sample size (analytical weights or cutoffs ranging from $n > 100$ to >300 with a $+50$ increment; see Kurdi & Banaji, 2017), (3) set of population control variables (i.e., $k = 0, 1, 2$, or 3), and (4) data transformation method (untransformed or log-transformed variables). This resulted in $6 \times 6 \times \binom{3}{k} \times 2 = 576$ possible model specifications.

We ran these 576 possible cluster-adjusted regression models and gathered the 576 standardized estimates associated with the effects of past proportion of Black residents. The median standardized estimate was different from zero $\bar{\beta} = .047$, 95% CI = [0.045, 0.049], $p < .001$; the direction of the effect was positive in nearly all cases, 98.26% [98.6%, 99.1%]; and the critical p value was below .05 in the clear majority of the models, 63.7% [59.6%, 67.6%]. As can be seen in Figure 3, this suggests that—despite variations from one model to another—the association was robust to model specifications.

Mediation Analysis

Next, we tested the mediational role of systemic inequalities using the same three variables that were found, in the South, to mediate the association between enslaved populations and implicit bias: (1) proportion of people living in poverty who are Black, (2) intergenerational economic mobility among Black residents, (3) racial residential segregation (Payne et al., 2019). Figure 4 offers a graphical representation of the finding. Proportion of Black residents in 1930 was a positive predictor of structural inequality circa 2010, $\beta = 0.75$, 95% CI = [0.66, 0.85], $p < .001$ (*a* path), which itself was a positive predictor of implicit bias, $\beta = 0.61$, 95% CI = [0.43, 0.79], $p < .001$ (*b* path). The association between proportion of Black residents in 1930 and implicit bias became nonsignificant when including structural inequality, $\beta = 0.07$, 95% CI = [−0.13, 0.28], $p = .479$ (*c'* path). The indirect effect—calculated using the percentile bootstrap method with 10^4 resamples (Yzerbyt et al., 2018)—was positive, *indirect* = 0.39, 95% CI = [0.10, 0.76], $p = .003$. Although these analyses cannot establish causality, they are consistent with the hypothesis that demographic population characteristics in the North and West during the Great Migration led to structural

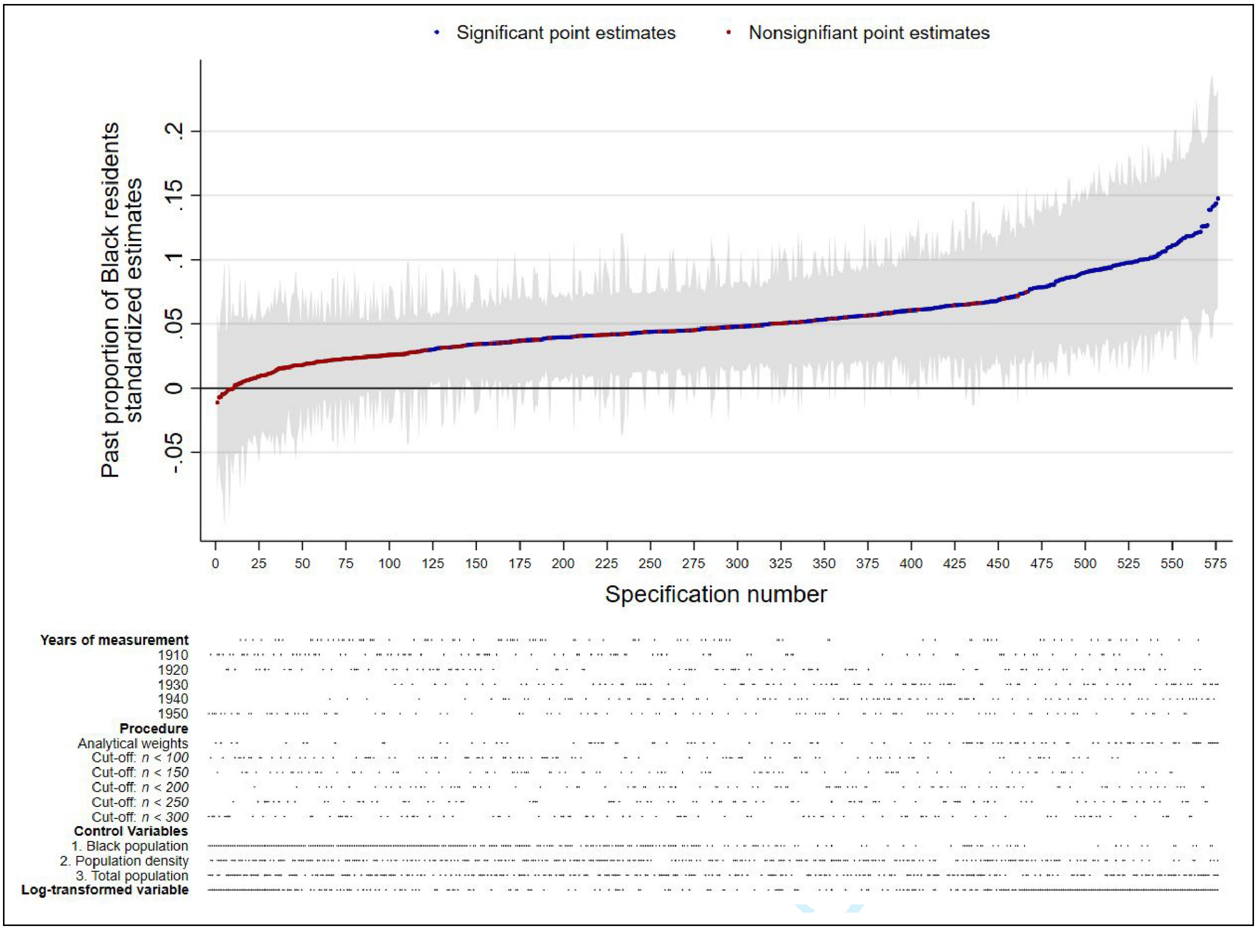

Figure 3. *Standardized Coefficient Estimates From a Specification Curve Analysis Testing the Effect of Past Proportion of Black Residents on Current Implicit Bias in 576 Models*

Note. The upper panel plots the standardized coefficient estimates of the focal effect in increasing order of magnitude for the 576 models; it can be seen that most of the coefficients are positive (98%) and significant (64%). The lower panel of the figure shows the model specifications; each dot indicates the specification that was used to produce the standardized coefficient estimates in the upper panel (e.g., the first specification, which is associated with the smallest coefficient in the upper panel, used 1950 as the year of measurement, a cutoff of $n < 300$, controlled for total population, and used log-transformed variables); it can be seen that the pattern of distribution of these dots is generally not systematic, meaning that model specification did not exert a clear-cut influence on estimation. Shaded areas represent 95% confidence intervals.

inequalities that in turn trigger higher levels of implicit bias in those counties today.

Discussion

We examined how the Great Migration set the stage for regional differences in implicit and explicit bias. For White respondents, the average implicit preference for White over Black individuals today was higher in counties that experienced larger-sized Black populations mid-century. This effect was statistically mediated by regional differences in structural inequalities. Counties with larger proportions of Black residents during this historical period became more residentially segregated, had larger proportions of Black individuals among the poor, and had less economic mobility among Black residents. These indirect effects are consistent with theories of implicit bias as a reflection of systemic racism in the environment (Payne & Hannay, 2021).

Explicit bias, in contrast, was lower in counties with larger Black populations. This negative correlation contrasts with the positive correlation between Black populations and explicit bias that has been documented in the South (Payne et al., 2019). Lower explicit bias in areas with larger Black populations is consistent with the contact hypothesis, which suggests that greater inter-racial interaction can reduce prejudice, at least under certain conditions (Paluck et al., 2019; Pettigrew & Tropp, 2006). The fact that the associations were stronger in more recent decades is consistent with the idea that it is present-day experiences rather than historical patterns that are responsible. Recent research examining regional variation in populations

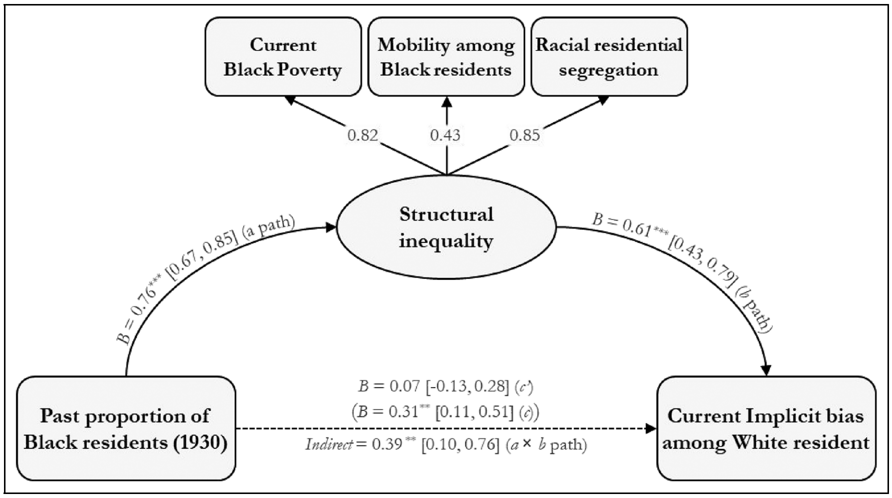

Figure 4. *Indirect Effect of Black Population in 1930 on Implicit Bias Among White Residents via Structural Inequality*
Note. Mediation model showing that county-level structural inequality statistically explain part of the association between the proportion of Black residents in 1930 and implicit bias among White respondents in 2002–2018. The total effect is given in parentheses. The total effect is slightly different from that of the regression analysis because our SEM uses LM rather than OLS as a method of estimation, and because of listwise deletion (i.e., missing values on the observables variables related to structural inequality). Number in brackets are 95% confidence intervals.
$^{***}p < .001$. $^{**}p < .01$.

suggests that the effect of Black populations on White prejudice depends on the degree of positive inter-group contact (Rae et al., 2015). It is possible that present-day interracial contact in the Northern and Western states examined here is more positive than in Southern states. If so, this difference might explain why larger modern-day Black populations are associated with lower explicit bias in the North and West but greater explicit bias in the South. Future research should examine this question further.

For Black respondents, larger Black populations were associated with a larger preference for Black over White individuals on both implicit and explicit measures. One interpretation of this correlation is consistent with the contact hypothesis. Areas with larger Black populations may lead to less inter-racial contact with White residents, and hence less positive out-group attitudes. Another interpretation is that larger Black populations lead to more positive in-group contact and positive in-group regard among Black residents (Welch et al., 2001). Because the IAT is a relative measure, we are not able to distinguish between negative out-group attitudes and positive in-group attitudes in these data.

A third interpretation is that inequalities—which are more pronounced in places with larger Black populations—may cue racial discrimination in the minds of Black residents, leading to implicit preferences for Black over White people. Consistent with previous work (Payne et al., 2019), we found that greater structural inequality was associated with stronger anti-White (or pro-Black) biases among Black respondents. In this and previous work, however, historical events were less relevant to bias compared with more contemporary population characteristics. Overall, the findings suggest that White individuals are more susceptible to historical legacies, whereas Black individuals are more attuned to the contemporary context. Further research is needed to understand why this is the case. One possibility is that a racist historical context generates more individualistic explanations for inequality, which White people readily use when interpreting a situation. In contrast, Black people may more readily use structural explanations because of personal experiences, community experiences, or contemporary antiracist movements. Research has found that White people indeed tend to endorse more individualistic explanations for racial inequality compared with Black people, who tend to endorse more structural explanations (Hunt, 2007; Pew Research Center, 2016).

The correlational nature of these data prevents us from drawing causal conclusions, although the time series nature of the Census data provides some information about temporal precedence. Our emphasis on historical processes led us to focus on one direction of the theoretical causal arrow, but implicit biases can also contribute to the maintenance of structural inequalities insofar as they result in increased discrimination and reduced readiness to dismantle racist structures. Our measures of structural inequality were based on data that are representative of the general population, but implicit and explicit attitude variables from Project Implicit are based on an opt-in sample. Project Implicit is, however, the only source of data available for measuring biases at the level of counties and states and it represents millions of U.S. residents. Our mediation findings suggest that present-day structural inequalities may cue implicit biases. However, we cannot identify what aspects of modern social and physical environments cue biases. Future research should examine the environmental cues that connect inequalities in the social environment to implicit associations in the minds of residents.

The most novel and distinctive finding in the present research is the positive association between Black populations in the early and mid-20th century and implicit bias among White residents. Explicit measures among White residents, and both explicit and implicit measures among Black residents revealed negative associations that were driven by recent decades. Implicit bias among White residents, however, followed a pattern similar to that observed with enslaved populations in the South. This pattern emerged decades later in the North and West, however, as the Great Migration brought Black Americans to Northern and Western cities in unprecedented numbers. These results suggest that the foundation for implicit bias among White residents outside the south was laid decades ago and is embedded in the structural inequalities that characterize modern spaces.

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Supplemental Material

The supplemental material is available in the online version of the article.

Notes

1. Alaska, Arizona, California, Colorado, Connecticut, Delaware, Hawaii, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Maine, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Dakota, Utah, Vermont, Washington, West Virginia, Wisconsin, Wyoming.
2. Commuting zones were nested within counties, meaning there was one commuting zone per county.

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