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County-Level Rates of Implicit Bias Predict Black-White Test Score Gaps in U.S. Schools

AUTHORS

Francis A. Pearman, II

Stanford University

ABSTRACT

This study examines whether county-level estimates of implicit bias predict black-white test score gaps in county schools. Data from over 1 million respondents from across the United States who completed an online version of the Race Implicit Association Test (IAT) were combined with data from the Stanford Education Data Archive covering over 300 million test scores from U.S. schoolchildren in grades 3 through 8. In both bivariate and multivariate models, counties with higher levels of racial bias had larger black-white test score disparities. This relationship was primarily explained by sorting mechanisms: The black-white test score gap was larger in counties with higher levels of implicit bias because these counties' schools were more racially segregated and were characterized by larger racial gaps in gifted and talented assignment as well as special education placement.

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County-Level Rates of Implicit Bias Predict Black-White Test Score Gaps in U.S. Schools

Introduction

Black-white disparities in educational outcomes remain persistent features of U.S. schooling (Reardon, Kalogrides, & Shores, 2019; Shores, Kim, & Still, in press). Scholars have proposed a number of structural explanations for these disparities, including inequitable funding, residential segregation, socioeconomic differences, and differential exposure to teachers and schools of varying quality (Gregory, Skiba, & Noguera, 2010; Jennings, Deming, Jencks, Lopuch, & Schueler, 2015; Quillian, 2003; Sosina & Weathers, 2019). For perhaps just as long, however, scholars have theorized and demonstrated that implicit racial bias, i.e., relatively unconscious associations regarding race, can also contribute meaningfully to racial disparities in educational outcomes (Carter, Skiba, Arredondo, & Pollock, 2017; Copur-Gencturk, Cimpian, Lubienski, & Thacker, 2019; Milner, 2015; Warikoo, Sinclair, Fei, & Jacoby-Senghor, 2016).

Much of the empirical literature on how implicit bias figures into the production of racial inequality in schools has focused on dyadic, teacher-student interactions in classroom or laboratory settings (Jacoby-Senghor, Sinclair, & Shelton, 2016; McKown & Weinstein, 2008; Okonofua, Paunesku, & Walton, 2016; Rubie-Davies, Hattie, & Hamilton, 2006; van den Bergh, Denessen, Hornstra, Voeten, & Holland, 2010). These studies generally find that racial disparities are worse when children are taught by or work with adults who exhibit higher levels of implicit bias. However, there is far less scholarship examining implicit bias as a community-level phenomenon. This oversight is notable considering growing evidence that aggregate measures of implicit bias predict racial disparities on key social, health, and economic outcomes.

For instance, Hehman, Flake, and Calanchini (2018) found that lethal force in policing against Black Americans is higher in metro areas in which residents evince higher levels of implicit bias—that is, bias not necessarily on the part of the police force, per se, but bias in the cities in which they operate. Chetty, Hendren, Jones, and Porter (2018) found that among black and white children who grow up in low-poverty counties that gaps in eventual labor market earnings are larger in counties with higher levels of racial bias against blacks. Finally, Leitner, Hehman, Ayuk, and Mendoza-Denton (2016) found evidence of greater Black-White disparities in circulatory disease in counties where whites reported greater racial bias against blacks. In short, racial disparities on a range of important outcomes appear worse in places with more racial bias (Eberhardt, 2019).

However, there is limited evidence about how racial bias, measured at the community level, relates to the nature and extent of educational disparities. One study to date has integrated into an analysis of racial inequality in schools aggregate measures of implicit bias. Riddle and Sinclair (2019) drew on cross-sectional data from the universe of U.S. public schools and examined the relation between racial bias, measured at the county-level, and discipline disparities between black and white students. They found that the amount of racial bias in schools' surrounding counties was positively associated with discipline disparities between black and white students. This finding indicates that the mechanisms connecting racial bias to racial inequality in schools may exist or originate, at least partly, in schools' broader community, although the mechanisms themselves are still poorly understood.

The current study expands this research by considering another dimension of educational inequality—test score disparities between black and white students—and directly testing what factors might be responsible for this relationship. In particular, this study asks the following research questions: Are test score gaps between black and white students larger in places with higher amounts of implicit bias against blacks? If so, does this relationship persist after accounting for observable differences across counties? And, finally: What schooling inputs might explain why places with more implicit bias have larger black-white test score gaps?

Background

There are several reasons why county-level estimates of implicit bias could be associated with black-white test score gaps. First, county-level estimates of implicit bias could be related to test score gaps by way of its relation to the structural conditions of schools. For instance, school segregation and black-white funding disparities may be worse in counties with higher levels of implicit bias. This could arise because white households in biased counties may be especially likely to self-segregate into non-traditional or private schools or because school assignment policies that integrate children by race may be deemphasized in such counties (Siegel-Hawley, Diem, & Frankenberg, 2018). Given the robust link between racial segregation, school funding, and achievement disparities (Reardon, 2016; Sosina & Weathers, 2019), it is plausible that implicit bias may be related to test score gaps because of increased between-school segregation or worse funding disparities in biased counties.

Second, implicit bias could be associated with test score disparities because children attending schools in counties with elevated levels of bias may experience differential treatment based on race. Differential treatment could manifest, for instance, in increased rates of punishment for black relative to white students (Gregory et al., 2010), an increased likelihood that black children are designated as in need of special education services (Annamma, Connor, & Ferri, 2013), or an increased likelihood that white children are assigned to gifted and talented programs (Tenenbaum & Ruck, 2007). Moreover, recent research has shown that these racial disparities in treatment are linked through decisions on the part of school personnel that can reinforce "categorical inequality" in schools and exacerbate test score disparities (Shores et al., forthcoming).

In sum, an association between county-level estimates of implicit bias and black-white test score gaps could come about for structural reasons, such as increased segregation or greater black-white disparities in school funding, or by way of reasons related to how students are differentially treated in school, as evidenced by such disparities as black-white gaps in punishment, gifted and talented assignment, or special education placement.

Data

To examine the relation between county-level estimates of implicit bias and black-white test score gaps, this study combines data from several sources. Test score data were obtained from the Stanford Education Data Archive, data on implicit bias were gathered from the Race Implicit Association Database, and supplementary datafiles were gathered from the Civil Rights Data Collection, National Center for Educational Statistics, and American Community Survey.

Black White Test Score Gap

This study gathers data on black-white test score gaps from the Stanford Education Data Archive V3.0. SEDA is constructed using the National Center for Educational Statistics *EDFacts* database, which provides counts of the number of children (overall and by race) scoring at different proficiency levels (e.g., below proficient, proficient, advanced) based on each state's standardized assessment of achievement. SEDA then combined these data with information from the National Assessment of Educational Progress to provide comparable test scores for every school district, county, and metropolitan area in the United States. These data are based on over 300 million test scores and are available annually for grades 3 through 8 from 2008 to 2016. To increase precision, estimated test score gaps in this study were pooled across survey years and across grades 3 through 8 for ELA and Math. The result was a single estimate of the black-white test score gap during the observation period.

This study focuses on Black-White test score disparities at the county level. Counties are the focus because counties are the geographical unit for which geocoded implicit bias data were available (more detail provided in the next section). Of note, SEDA restricted test score gap information to those counties that contain at least 20 Black students and 20 White students. Consequently, of the 3,142 counties in the United States, 2,088 were included in the analytic sample. This restricted sample of counties nevertheless includes 96% of Black public school students in grades 3 through 8 nationwide. That two-thirds of U.S. counties contain nearly all Black students nationwide is evidence of the high degree of racial segregation that still plagues U.S. school systems.

Implicit Bias

This study gathers data on implicit bias from over one million respondents from across the United States who voluntarily completed an online version of the Race Implicit Association Test (IAT) between 2008 and 2016 (the same period for which test score data were gathered). The IAT is a dual categorization task that captures the difference in a participant's ability to associate positive and negative words with white versus black faces and is the most widely used and well-validated measure of implicit bias (Greenwald, McGhee, & Schwartz, 1998). These individual, online-based assessments were recently made publicly available through Project Implicit (Xu, Nosek, & Greenwalk, 2014). The current study uses these data but limits the sample to respondents who identified as white, had geographic information that allowed them to be geocoded to a U.S. county and took the assessment between 2008 and 2016 (during the same period for which the racial test score gap was observed). This resulted in a sample of 1.2 million implicit bias assessments from individual respondents in every county in the United States.

Given that the use of web-based data drawn from a voluntary sample raises concern about representativeness, multiple regression with post-stratification (MRP) was used to create more accurate geographical population-based estimates of implicit bias (Park, Gelman, & Bafumi, 2004). In particular, county-level estimates of implicit bias were estimated based on population cells defined by a cross-classification of geography and demographics. Respondents were first grouped into four education-bins (less than high school degree, high school degree, some college, and bachelor's degree or higher) for males and females, respectively, resulting in eight demographic categories. Next, multilevel regressions were fit in which implicit bias was treated as a function county-level characteristics, and these estimates were allowed to vary by the education level of respondents, sex of respondents, and the county, state, and region of the country, respectively, in which respondents were surveyed.

Next, this estimated model was used to predict the expected level of bias for each demographic category (e.g., male high school graduate, female college graduate, etc.) in each county. The final county-level estimates of implicit bias were the predicted values of implicit bias for each demographic category in each county weighted by the population of the respective demographic category in that county.[1] The result of this weighting strategy was a more generalizable estimate of implicit bias. (Figure A.1 in the Appendix provides coefficient estimates from the MRP models; Table F.1 in the Appendix provides a series of robustness checks for alternative specifications of the MRP model and for disaggregated county means of IAT scores that do not account for demographic or geographical variation.)

Control Variables

Control variables were included for a number of school and community characteristics. The inclusion of these control variables allows for a clearer picture of the relation between racial bias and test score gaps by equalizing counties along dimensions that might otherwise be related to implicit bias (e.g., socioeconomic differences between black and white households in a county) and reducing unexplained variance in test score gaps. This study controls for the following characteristics of county schools: the total number of students in grade 3 through 8, the percent

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[1] Population counts for demographic categories were averaged across American Community Survey's 5-year estimates ending in 2009, 2010, 2011, 2012, 2013, 2014, 2015, and 2016.

of students who are white, black, Latinx, and eligible for free-and-reduced-price lunch, respectively, and the share of schools located in urban areas. These data were gathered from the Stanford Education Data Archive and were averaged across school years 2008-09 through 2015-16. This study also controls for the following community-level characteristics: between-neighborhood racial segregation, crime rates, and overall as well as black-white differences in median income, percent of adult residents who have obtained a bachelor's degree or higher, percent unemployed, percent receiving SNAP, percent living in poverty, and percent of families led by single mothers. These characteristics were gathered from the American Community Survey and were averaged across the following survey years: 2006-10, 2007-11, 2008-12, 2009-13, 2010-14, 2011-15, and 2012-2016. (See SEDA technical documentation [Fahle et al., 2018] for further description of covariates).

Method

Given that the structure of the SEDA data includes multiple observations per county (county test score for black and white students, respectively), this study examines the relation between the black-white test score gap and county-level estimates of implicit bias by specifying a hierarchical linear model of the following form:

$$\begin{aligned}
\hat{Y}_{rcs} &= \alpha_{0cs} + \alpha_{1cs} Race + e_{rcs} + \varepsilon_{rcs} \\
\alpha_{0cs} &= \beta_{00s} + \beta_{01s} Bias_{cs} + \beta_{0.s} X_{cs} + r_{0cs} \\
\alpha_{1cs} &= \beta_{10s} + \beta_{11s} Bias_{cs} + \beta_{1.s} X_{cs} + r_{1cs} \\
\beta_{00s} &= \gamma_{000} + u_{00s} \\
\beta_{01s} &= \gamma_{010} + u_{01s} \\
\beta_{10s} &= \gamma_{100} + u_{10s} \qquad (1)
\end{aligned}$$

$\beta_{11s} = \gamma_{110} + u_{11s}$

$\beta_{0.s} = \gamma_{0.0}$

$\beta_{1.s} = \gamma_{1.0}$

$\varepsilon_{rcs} \sim N(0, \omega_{rcs}^2)$; $e_{rcs} \sim N(0, \tau_1^2)$;

$r_{cs} \sim MVN(0, \tau_2^2)$; $u_s \sim MVN(0, \tau_3^2)$

where $\hat{Y}_{rcs}$ is an estimated standardized measure of achievement for racial group r in county c in state s; $Race$ is an indicator for racial group (white or black students with black students serving as the referent category), $Bias_{cs}$ is a measure of the amount of implicit bias in county c in state s standardized to have a mean of zero and standard deviation of 1; X_{cs} corresponds to a vector of county-level covariates in state s (X_{cs} is excluded in unadjusted models). The $r_{.cs}$ are multivariate normally distributed mean-zero county-level residuals with variance-covariance matrix τ_2^2 to be estimated; the $u_{.s}$ are multivariate normally distributed mean-zero state-level residuals with variance-covariance matrix τ_3^2 to be estimated; e_{rcs} is a normally distributed within-county residual with variance-covariance matrix τ_1^2 to be estimated; and ε_{rcs} is a normally distributed mean-zero error term with variance equal to ω_{rcs}^2, which is the known sampling variance of $\hat{Y}_{rcs}$. Model estimation was performed using maximum likelihood in HLM v8 software.

The coefficient of interest, β_{11c}, pertains to a cross-level interaction term and provides an understanding of the extent to which the test score gap between black and white students depends on the level of implicit bias in a county; positive values indicate there is a positive association between bias and the racial test score gap. Of note, α_{0rcs} is interpreted as the relation between a 1-standard deviation increase in implicit bias and the test scores for black students, while the linear combination of α_{0rcs} and β_{11c} is interpreted as the relation between a 1-standard deviation increase in implicit bias and test scores for white students.

In addition to examining bivariate and multivariate relations between black-white test score gaps and county-level estimates of racial bias, this study is also interested in potential explanations for why such a relation may exist. This study sheds light on this question by examining the extent to which several schooling inputs might account for why places with more implicit bias have larger black-white test score gaps. The objective is to focus on schooling inputs that are (a) plausibly related to racial bias, and (b) reasonably under the control of school systems. This study focuses on five such schooling inputs identified in the background section of this article: between-school racial segregation, funding disparities between black and white students, the black-white discipline gap, the black-white gap in gifted assignment, and the black-white gap in special education placement.[2]

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[2] Between-school *racial segregation* captures differences in exposure to white students at the average school attended by black versus white students. This variable was gathered from the Stanford Education Data Archive and was average across NCES datasets between 2008 and 2016. The remaining schooling inputs were gathered from the Civil Rights Data Collection (CRDC) and were averaged across the 2011-12, 2013-14, and 2015-16 surveys. *Racial disparities in school funding* were measured as the mean difference in per-pupil expenditures at the school attended by the average white compared to the average black student in a county. *Racial discipline gaps* were measured as the difference in suspension rates between black and white students in each county. *Gifted placement gaps* were measured as the difference in rates of gifted assignment for white versus black students in each county. *Special education gaps* were measured as the difference in rates of special education placement for black versus white students in each county. Each variable capturing a racial disparity is scaled such that higher scores signal more favorable outcomes for white students. The county schools included in the measurement of each schooling input are restricted to those schools containing at least one grade

To model the extent to which the relation between black-white test score gaps and county-level estimates of implicit bias was explained by schooling inputs, Equation (1) was modified to include each schooling input, in turn, in the vector of county-level characteristics, X_{cs}. (Each schooling input is included in a separate regression.) Of interest in these exploratory models is the change in the coefficient for the interaction term between implicit bias and racial group after the inclusion of the interaction between schooling input and racial group.

Results

Descriptive Statistics

Table A.1 in the Appendix provides descriptive statistics for test scores by race, implicit bias, and all included covariates. The average achievement for black and white students is -0.42 and 0.11 standard deviations, respectively, corresponding to a black-white test score gap 0.53 SDs across the analytic sample. With respect to the key predictor variable, the unstandardized county-level estimates of implicit bias adjusted with poststratification show a pro-white bias nationwide (mean = 0.40, sd = 0.02) (where zero equals no bias).

Figure 1 illustrates a scatterplot of the unadjusted association of academic achievement and county-level estimates of implicit bias for black versus white students.[3] The navy points refer to white students, and the grey points refer to black students. Each point in the figure

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level between 3 and 8. Therefore, most elementary and middle schools are included in the measurement of each schooling input.

[3] For descriptive purposes, test scores in Figure 1 were adjusted using a "shrunken" Empirical Bayes (EB) technique to minimize the influence of counties with relatively imprecise estimates of test scores (Fahle et al., 2019).

refers to a county; the size of each point is proportional to the number of black and white students, respectively, in the county. The y-axis refers to test scores, which are standardized, and the x-axis refers to county-level estimates of implicit bias, which are also standardized.

Moving from the left to the right of the figure, the trend lines for black and white students diverge slightly, suggesting a potential positive gradient between racial test score disparities and county-level estimates of racial bias. That is, as the amount of implicit bias increases, the gap in test scores between black and white students also appears to increase. Moreover, both trend lines slope downward, suggesting that achievement for black and white students may be lower for both racial groups in more biased counties. (These observations are evaluated statistically in the next section.) Note also the relatively tight clustering of points around the trend line. Indeed, the r-squared corresponding to the figure (assessed as the relation between achievement and implicit bias in which the relation is allowed to vary by race) is 0.61.

Bivariate and Multivariate Models

Figure 2 displays coefficient estimates for unadjusted and adjusted regressions of test score gaps on county-level rates of implicit bias. From left to right, the first set of three bars refers to unadjusted estimates, while the last set of bars refers to adjusted estimates. As indicated in the unadjusted model, a 1 standard deviation increase in county-level estimates of implicit bias is associated with a black-white test score gap that is 0.029 standard deviations larger ($p = .020$). This association is explained by the fact that county-level estimates of implicit bias are also associated with lower achievement for black students (β = -0.029, $p =$

.002). No evidence is found that county-level estimates of bias are associated with changes in the test score of white students.

The right set of bars indicates that even after adjusting for observable differences across counties, for such things as socioeconomic composition, crime rates, residential segregation, and demographics of county schools, county-level estimates of implicit bias still predict black-white test score disparities. In particular, a 1 standard deviation increase in county-level estimates of implicit bias is associated, in fully-adjusted models, with an increase in black-white test score disparities of 0.020 ($p = .020$) standard deviations. In contrast to what was observed for the unadjusted models, however, there is no clear evidence whether the statistically significant association between the test score gap and county-level estimates of implicit bias is driven by changes to the test scores of black or white students.

Figure 3 turns attention to the question of the schooling inputs that might help illuminate the association between implicit bias and the black-white test score gap. In particular, Figure 3 displays point estimates for the coefficient of interest from Equation (2) (the interaction term between implicit bias and race) in a series of models in which each schooling input is added, in turn.[4] Reported estimates from the primary analysis are provided in the first row.

[4] Table D.1 in the Appendix displays results from a correlation matrix between implicit bias and each schooling input. Counties with elevated rates of implicit bias against blacks have greater amount of between-school segregation, larger black-white discipline gaps, assign more black than white students with special education designations, and assign fewer black than white students to gifted and talented programs. No association is observed between county-level estimates of implicit bias and black-white funding disparities.

Black-white funding disparities provide no predictive explanation, while the black-white discipline gap explains 14% of the association between county-level estimates of implicit bias and the black-white test score gap. Far more predictive are differences in how schools sort (and label) students. Between-school racial segregation explains one-third of the relation between county-level estimates of implicit bias and test score disparities. Notably, the predictive explanation of between-school segregation is above and beyond that associated with between-*neighborhood* segregation, which is controlled for in the model. Finally, black-white disparities in gifted and talented assignment explain 54% of the observed relation, while virtually the entirety of the observed associations between county-level estimates of racial bias and test score disparities is explained by black-white differences in special education assignment.

Discussion

This study set out to document whether a relation exists between county-level estimates of implicit bias and black-white test score disparities. Overall, this study finds evidence that the two are positively related. Counties with a 1 standard deviation increase in bias against blacks have a black-white test score gap that is 0.020 standard deviations larger, even after accounting for a host of observable differences across counties. To gain some appreciation for the magnitude of this association, consider that this magnitude is roughly equivalent to the size of the association between test score gaps and racial gaps in family income and about one-half the size of the association between test score gaps and residential segregation (see Table B.1 in the Appendix for full regression results). In other words, although the magnitude of the relation between the black-white test score gap and county-level estimates of implicit bias is substantively small, the magnitude is nonetheless on par with other widely accepted predictors of black-white test score disparities.

This study also found evidence that the relation between test score disparities and racial bias can be explained, in large part, by sorting mechanisms. In particular, test score gaps are larger in counties with elevated levels of bias because these counties have (a) more segregated schools, (b) increased proportions of white students in gifted and talented programs, and (c) increased proportions of black students with special education designations. In fact, the entirety of the point estimate for the association between racial bias and test score gaps was accounted for when including in the analytic model black-white gaps in special education assignment. The other notable explanation for why black students performed increasingly worse than white students on achievement tests as levels of implicit bias increased in their surrounding county is that schools in counties with elevated levels of bias suspend black students at elevates rates compared to white students.

Although this study provides novel insight into whether and why county-level estimates of implicit bias predict black-white test score gaps, it is important to acknowledge several limitations of this study. First, although this study used data from over 1 million respondents who completed an online bias survey along with post-stratification techniques to make estimates of implicit bias more generalizable, there are unobserved ways in which respondents to the bias survey may not have been representative of the general population of white people in each county. Second, this study's design prevented any causal claims regarding the directional relation between implicit bias and test score gaps. In particular, it is possible that living in a county with larger black-white test score gaps may exacerbate existing racial stereotypes, that the relation may be bidirectional, or that the association between bias and racial test score gaps may be driven by unobserved factors.

Nevertheless, this study complements prior laboratory and classroom studies of the relation between implicit bias and racial test score disparities by showing that the black-white test score gap is larger in counties in which whites exhibit greater levels of unconscious bias against blacks, and by showing that this association is due to how implicit bias, measured at the county level, relates to discipline disparities in school, between-school racial segregation, and the way schools operationalize and institutionalize notions of giftedness and special needs. A critical examination of how implicit bias influences the practices, policies, and procedures that govern exclusionary discipline, school assignment, and the labelling of gifted versus special needs could be a first step in creating more equitable educational systems that give black children a better chance to succeed.

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Figure 1: Scatter Plot of Achievement by Race and County-Level Estimates of Implicit Bias

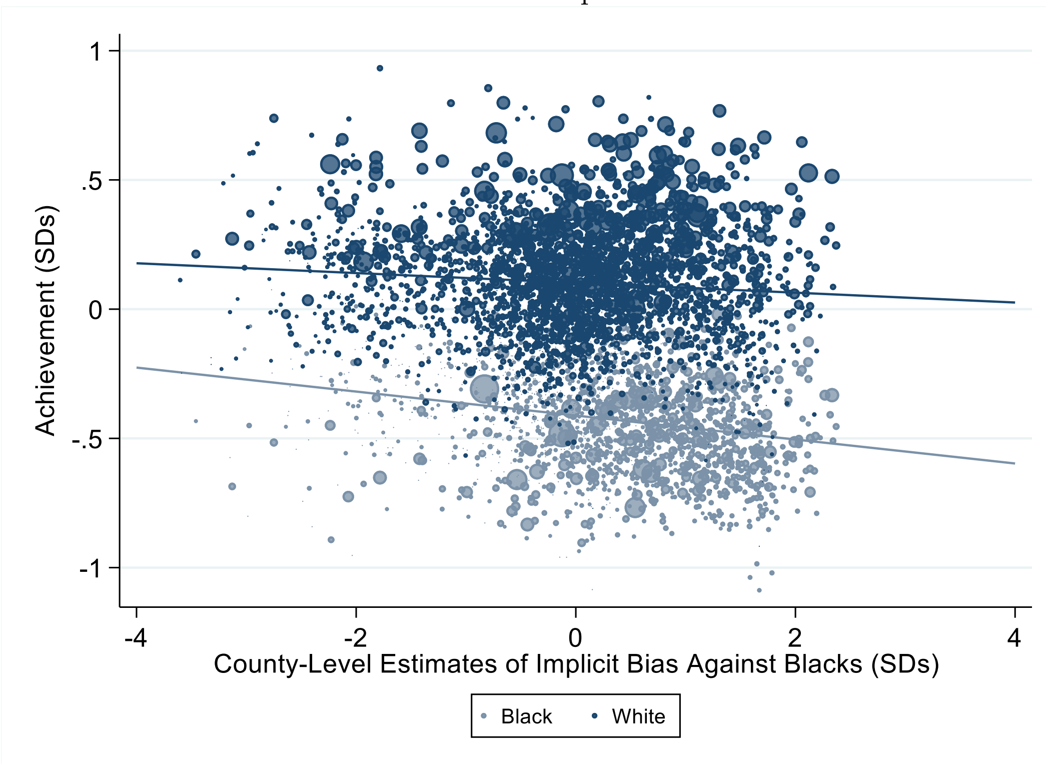


Figure 2: Unadjusted and Adjusted Relationship Between Test Scores and County-Level Estimates of Implicit Bias

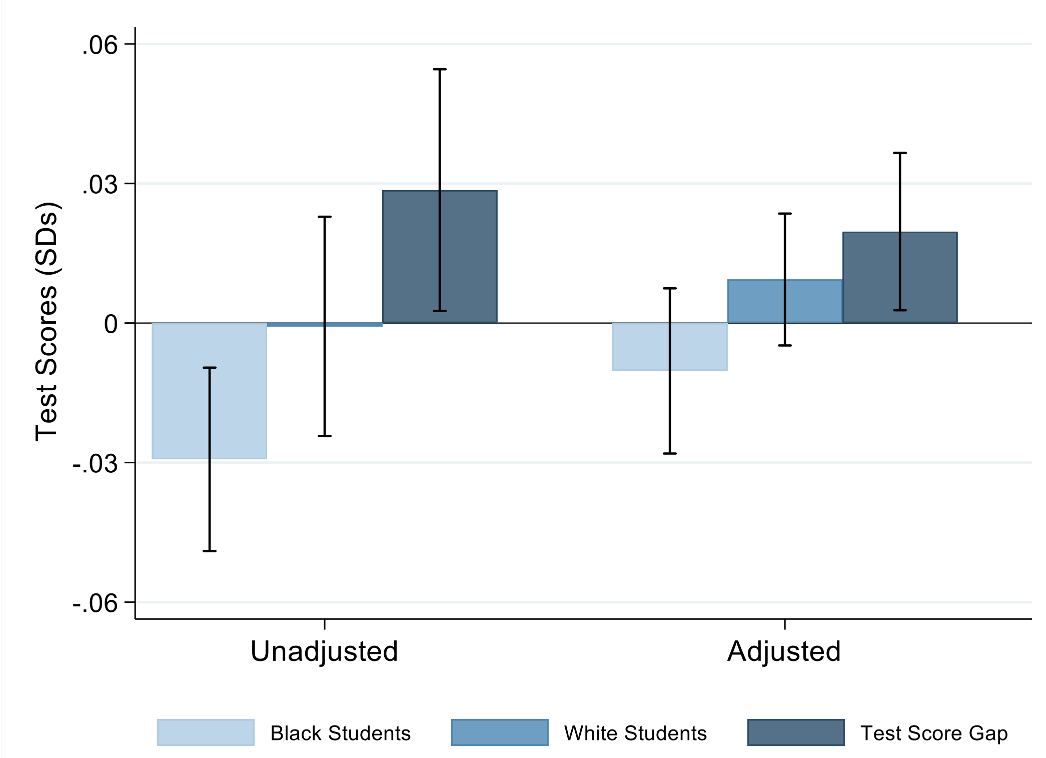
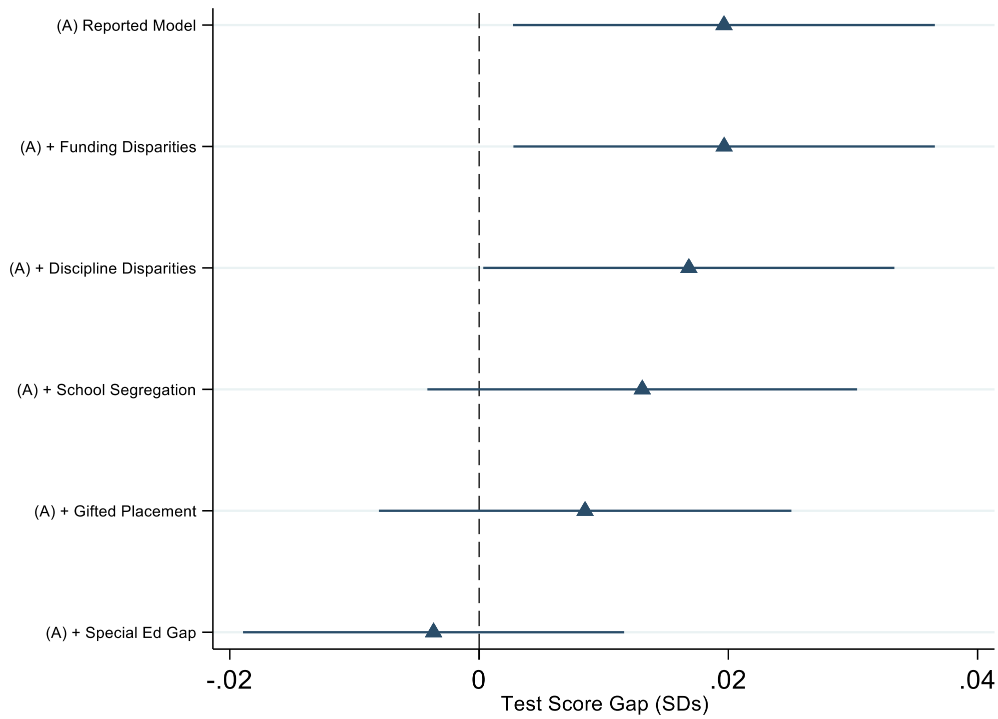


Figure 3: Adjustments to the Association Between Test Score Gaps and County-Level Estimates of Implicit Racial Bias Based on Schooling Inputs



Appendix

Table A.1: Descriptive Statistics

	Mean	*SD*
Implicit Bias	0.40	0.02
Test Scores (SDs)		
Black Students	-0.42	0.21
White Students	0.11	0.22
School Characteristics		
% Black	0.68	0.24
% White	0.16	0.21
% Latinx	0.12	0.16
Total Enrollment	10,157	28,630
% FRPL	0.56	0.16
Urban	0.11	0.25
Community Characteristics		
Segregation	0.10	0.12
Crime Rate (Per 100,000)	576.95	352.50
log(Median Income)	10.73	0.25
% Bachelors or Higher	0.16	0.08
% Unemployed	0.08	0.02
% SNAP	0.14	0.05
% Poverty	0.16	0.06
% Single Mother	0.18	0.05
Black-White Differences		
log(Median Income)	0.48	0.23
% Bachelors or Higher	0.10	0.08
% Unemployed	0.07	0.03
% SNAP	0.17	0.07
% Poverty	0.17	0.07
% Single Mother	0.28	0.07
n=	4,176	

FIGURE B.1: FULL RESULTS FROM REGRESSION OF ACADEMIC ACHIEVEMENT ON COUNTY-LEVEL ESTIMATES OF IMPLICIT RACIAL BIAS AND OTHER CHARACTERISTICS

	Unadjusted	*Adjusted*
County-Level Bias	-0.029**	-0.010
	(0.009)	(0.009)
White	0.544***	0.517***
	(0.016)	(0.009)
Bias x Race	0.029*	0.020*
	(0.012)	(0.008)
<u>School-Level Characteristics</u>		
% White		0.013
		(0.018)
% White x Race		-0.049**
		(0.017)
% Black		0.004
		(0.015)
% Black x Race		-0.034*
		(0.014)
% Latinx		0.012
		(0.013)
% Latinx x Race		0.009
		(0.012)
Total Enrollment		0.007*
		(0.003)
Total Enrollment x Race		0.003
		(0.003)
% FRPL		-0.057***
		(0.010)
% FRPL x Race		-0.042***
		(0.010)
Urban		-0.005
		(0.004)
Urban x Race		0.009**
		(0.003)

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Figure B.1: Continued

	Unadjusted	*Adjusted*
<u>Community-Level Characteristics</u>		
Segregation		-0.021***
		(0.005)
Segregation x Race		0.040***
		(0.004)
Crime Rate		-0.011*
		(0.004)
Crime Rate x Race		0.014**
		(0.004)
Median Income		0.009
		(0.014)
Median Income x Race		-0.036**
		(0.013)
% Bachelors or higher		0.031***
		(0.008)
% Bachelors or higher x Race		0.049***
		(0.008)
% Unemployed		0.003
		(0.006)
% Unemployed x Race		-0.014*
		(0.006)
% SNAP		0.022*
		(0.009)
% SNAP x Race		-0.017
		(0.009)
% Poverty		0.007
		(0.011)
% Poverty x Race		-0.015
		(0.010)
% Single Mother		-0.013
		(0.010)
% Single Mother x Race		0.009
		(0.009)

(Continued on next page)

FIGURE B.1: CONTINUED

	Unadjusted	*Adjusted*
Black-White Differences		
Median Income		-0.020***
		(0.005)
Median Income x Race		0.019***
		(0.005)
% Bachelors or higher		-0.013**
		(0.005)
% Bachelors or higher x Race		0.040***
		(0.004)
% Unemployed		-0.002
		(0.004)
% Unemployed x Race		0.007
		(0.004)
% SNAP		-0.029***
		(0.005)
% SNAP x Race		0.038***
		(0.005)
% Poverty		-0.007
		(0.005)
% Poverty x Race		0.003
		(0.005)
% Single Mother		-0.013*
		(0.005)
% Single Mother x Race		0.014**
		(0.005)
n =	4,176	4,176

Note: Covariates are standardized to facilitate interpretation. Standard errors are in parenthesis. *p<.05, **p<.01, ***p<.001 for two-tailed tests of significance.

Table C.1: Proportion of the Association Between Implicit Bias and Test Score Gaps Explained by School Funding Disparities, Discipline Gaps, Gifted Placement Gaps, Special Education Assignment Gaps, and Racial Segregation

	Reported (A)	*(A)+Funding Disparities (B)*	*(A)+Discipline Gap (C)*	*(A)+Racial Segregation (D)*	*(A)+Gifted Placement Gap (E)*	*(A)+Special Ed Assignment Gap (F)*
Implicit Bias	-0.010	-0.010	-0.008	-0.006	-0.004	0.010
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
White	0.517***	0.517***	0.513***	0.519***	0.524***	0.503***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.008)	(0.007)
Bias x White	0.020*	0.020*	0.017*	0.013	0.009	-0.004
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
Funding		-0.001				
		(0.003)				
Funding x White		-0.000				
		(0.003)				
Suspensions			-0.035***			
			(0.005)			
Suspensions x White			0.040***			
			(0.004)			
Segregation				-0.035***		
				(0.005)		
Segregation x White				0.056***		
				(0.005)		
Gifted Placement					-0.016**	
					(0.005)	
Gifted Placement x White					0.055***	
					(0.004)	
Special Education						-0.068***
						(0.005)
Special Education x White						0.080***
						(0.004)
n=		4,176	4,176	4,176	4,176	4,176
Proportion Explained		< 1%	14%	33%	57%	>99%

Note: This table provides estimates of the extent to which the association between implicit bias and test score disparities is accounted for by various schooling inputs. Proportion Explained is calculated as the difference in the coefficient of interest (Bias x Race) between each model and Model [A] divided by the coefficient in Column (A). All models are fully adjusted. Standard errors are in parenthesis. *p<.05, **p<.01, ***p<.001 for two-tailed tests of significance.

Table D.1: Correlation Matrix of County-Level Estimates of Implicit Bias, Black-White Test Score Gaps, and Racial Disparities in Schooling Inputs

	1	2	3	4	5	6	7
1. Implicit Bias	1.00***						
2. Academic Achievement	-0.10***	1.00***					
3. Funding Gap	-0.03*	0.01	1.00***				
4. Segregation	0.27***	-0.03	-0.02	1.00***			
5. Discipline Gap	0.18***	-0.09***	0.00	0.36***	1.00***		
6. Gifted Placement Gap	0.32***	0.03*	0.02	0.17***	0.12***	1.00***	
7. Special Ed. Assignment Gap	0.41***	-0.04*	-0.01	0.33***	0.18***	0.39***	1.00***

Note: *p<.05, **p<.01, ***p<.001 for two-tailed tests of significance.

Table F.1: Robustness Checks for Alternative Specifications of Post-Stratification Models

	MRP w/ Education & Sex (reported) (A)	MRP w/Age & Sex REs (B)	MRP w/ Education REs (C)	MRP w/Age REs (D)	Raw County Means (E)
Implicit Bias	-0.010	-0.008	-0.012	-0.007	-0.005
	(0.009)	(0.008)	(0.009)	(0.009)	(0.006)
White	0.517***	0.517***	0.517***	0.518***	0.514***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Bias x Race	0.020*	0.021*	0.023*	0.023*	0.012
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
n=	4,176	4,176	4,176	4,176	4,176

Note: All models are fully adjusted and include controls at the school and community level. All MRP models include random effects at the county, state, and region level. Each MRP model (A through D) differs in terms of the individual random effects included in the MRP model. Individual random effects are specified in the column name. Raw county means (Column E) are disaggregated county averages of IAT scores without accounting for demographic or geographical variation. Standard errors are in parenthesis. *p<.05, **p<.01, ***p<.001 for two-tailed tests of significance.

Figure A.1: Standardized Coefficient Estimates in Post-Stratification Models for County-Level Predictors of IAT Responses