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Collective Racial Bias and the Black-White Test Score Gap

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ABSTRACT

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Abstract: This study examines the relationship between county-level estimates of racial bias and black-white test score gaps in U.S. 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. Two key findings emerged. First, in both bivariate and multivariate models, counties with higher levels of racial bias had larger black-white test score disparities. The magnitude of these associations were on par with other widely accepted predictors of racial test score gaps, including racial gaps in family income and racial gaps in single parenthood. Second, the observed relationship between collective rates of racial bias and racial test score gaps was explained by the fact that counties with higher rates of racial bias had schools characterized by more segregation and larger racial gaps in gifted and special education placement. This pattern is consistent with a theoretical model in which collective rates of racial bias affect educational opportunity through sorting mechanisms that operate both within and beyond schools.

Collective Racial Bias and the Black-White Test Score Gap

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 racial bias. However, there is far less scholarship examining racial bias as a community-level phenomenon. This oversight is notable considering growing evidence that aggregate measures of racial 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 racial bias against blacks? If so, does this relationship persist after accounting for observable confounding factors? And, finally: What schooling inputs might explain why places with more racial bias have larger black-white test score gaps?

Background

Figure 1 displays a directed acyclic graph of the theoretical relations that may exist between aggregate rates of racial bias and black-white test score gaps. First, aggregate rates of racial bias could be related to test score gaps by way of their relations to the structural conditions of schools and resources available through them. For instance, between-school segregation (Arrows 1 and 2) and black-white disparities in school resources (Arrows 3 and 4) may be worse in counties with higher levels of racial 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 school segregation, school funding, and achievement disparities (Ashenfelter, Collins, & Yoon, 2006; Guryan, 2004; Johnson, 2011; Reardon, 2016; Sosina & Weathers, 2019), it is plausible that racial bias may be related to test score gaps because of increased between-school segregation, worse funding disparities, or even greater racial disparities in prekindergarten access in biased counties.

Second, as indicated by Arrows 5 and 6, aggregate rates of racial bias could be associated with test score disparities because of racial biases that manifest within school walls. Specifically, children attending schools in counties with elevated levels of bias may experience differential treatment in school based on race (Warikoo et al., 2016). 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; see also Pearman, Curran, Fisher, & Gardella, 2019;).

In addition to the indirect ways in which aggregate rates of racial bias could cause black-white test score gaps, it is also important to note potential confounds of these relations—that is, factors that might affect aggregate rates of racial bias while contributing to racial test score gaps. These distal factors are illustrated on the left of Figure 1. First are racial disparities in family resources. Black-white disparities are large on a range of socioeconomic factors, including educational attainment, wealth, and income (Rothstein & Wozny, 2013; Sirin, 2005). Moreover, these disparities can have a direct effect on racial test score gaps, as indicated by Arrow 8. In particular, higher resourced households (a) are better able to invest in and support their children's education through tutoring and other enrichment activities outside of school, (b) experience less parental stress and depression, and (c) have social and cultural capital that is more readily exchanged in the educational market (Bassok, Finch, Lee, Reardon, & Waldfogel, 2016; Bradley, Corwyn, McAdoo, & Garcia Coll, 2001; Chin & Phillips, 2004; Lareau, 2003; Phillips, 2011). Insofar as these factors are causally related to achievement—and given the stark black-white disparities in socioeconomic status just mentioned—it follows that these factors could be causally related to the black-white test score gap (Reardon et al., 2019).

In addition to black-white differences in family resources affecting black-white test score gaps, black-white differences in family resources may also contribute to aggregate rates of racial bias, as indicated by Arrow 9. This could arise if racial bias depends, in part, on perceived status differentials between racial groups. On the one hand, it is possible that racial bias may be smaller in counties in which white families live in relative socioeconomic parity with black households and perceive them as socioeconomic peers (see Bottero [2004] on class identities and lifestyle considerations). On the other hand, evidence suggests that socioeconomic parity between white and black households may actually foster racial animus among white households because of perceived threats to their social status (Bobo, 1999; Bobo & Zubrinsky, 1996; Pettigrew, 2017). Regardless of whether socioeconomic differences promote or mitigate racial bias, black-white disparities in family resources may nonetheless confound the relation between aggregate rates of bias and test score disparities because black-white differences in family resources may contribute to both.

Black-white disparities in family resources may also contribute to another confounding factor. As indicated by Arrow 10, disparities in family resources can contribute to racial disparities in residential conditions (Lareau & Goyette, 2014). Moreover, as illustrated by Arrow 11, these disparities in residential conditions can influence black-white test score disparities (Card & Rothstein, 2007; Wodtke, Yildirim, Harding, & Elwert, 2020). For instance, relative to children growing up in more affluent places, children growing up in high-poverty neighborhoods have limited exposure to institutional resources, as evidenced by lower quality schools and fewer health care clinics and libraries (Allard & Small, 2013; Brooks-Gunn, Johnson, & Leventhal, 2010; Dunn, Schaefer-McDaniel, & Ramsey, 2010; Hostinar & Gunnar, 2013), experience more stress due to heightened exposure to crime and violence, parental unemployment, and family instability (Brooks-Gunn et al., 2010; Sharkey, Schwartz, Ellen, & Lacoe, 2014; Sharkey, 2010), and experience greater exposure to harmful particulate matter and other environmental toxins (Camacho-Rivera, Kawachi, Bennett, & Subramanian, 2014; Crowder & Downey, 2010). Given the persistence and scope of racial residential segregation in the United States, these adverse residential exposures are disproportionately borne by black households and can contribute to black-white achievement disparities (Logan, 2011; Pattillo, 2013; Reardon, Fox, & Townsend, 2015; Sharkey, 2013).

Moreover, as indicated by Arrow 12, there is evidence that disparities in residential environments may contribute to patterns of racial bias. This pattern may arise, simply, because the places in which people live and the people they see and with whom they interact can shape their beliefs about other groups (Eberhardt, 2019). For instance, prior research has shown that white people living in areas with fewer black people, higher crime rates, less urbanization, and higher levels of segregation may be more likely to harbor racial animus against black people (Carter & Murphy, 2015; Cook, Logan, & Parman, 2018; Hurwitz & Peffley, 1997; Joyner & Kao, 2000; Taylor et al., 2013). Therefore, an observed relation between aggregate rates of racial bias and black-white test score gaps could come about because black-white disparities in residential conditions cause both.

There are a few other key points to make regarding the theorized relations between aggregate rates of racial bias and test score disparities displayed in Figure 1. First, the relation between each potential confounding factor (disparities in family resources and residential conditions, respectively) and racial bias is at the least bi-directional, as indicated by the dotted Arrows 14 and 15. For instance, aggregate rates of racial bias may exacerbate black-white disparities in socioeconomic status or residential conditions because black households looking to obtain employment or relocate to more favorable neighborhoods may face more discrimination in counties with higher levels of racial bias (Chetty et al., 2018; Rothwell & Massey, 2010). Second, in addition to the manifold ways in which aggregate rates of racial bias may affect black-white test score gaps, it is possible that black-white test score gaps can have a direct effect on aggregate rates of racial bias by exacerbating or reinforcing existing racial biases, as indicated by dotted Arrow 17.

In sum, an association between county-level estimates of racial bias and black-white test score gaps could come about for structural reasons, such as aggregate rates of racial bias affecting between-school segregation or black-white disparities in school funding, or by way of reasons related to the racial biases of school personnel or institutional practices as evidenced by such disparities as black-white gaps in punishment, gifted and talented assignment, or special education placement. However, a potential relationship between aggregate rates of racial bias and test score gaps arising through any of these proposed mechanisms could be confounded by racial disparities in family economic resources or disparities in residential conditions that together or independently contribute to both. Finally, reverse causality is plausible given that test score gaps could conceivably affect aggregate rates of racial bias by reinforcing or exacerbating existing racial stereotypes.

Data

To examine the relation between county-level estimates of racial 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 racial 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 (SEDA) 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 bias data were available (more detail provided in the next section). Of note, SEDA restricted test score gap information to those counties containing 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 (Reardon et al., 2019).

Racial Bias

This study gathers data on implicit racial bias from over one million respondents from across the United States who visited the Project Implicit website and voluntarily completed an online bias survey between 2008 and 2016 (Xu, Nosek, & Greenwalk, 2014). Implicit bias was measured based on the Race Implicit Association Test (IAT). The Race 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).[1] As a robustness check, this study also reports results in Appendix Table D.1 based on the degree of conscious or explicit racial bias measured as the difference in respondents' reported warmth toward white versus blacks people (where 0 equals very cold and 10 equals very warm) (see Leitner et al., 2016). This study uses the entire publicly available dataset from Project implicit 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 roughly 1.4 million respondents spread across 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

[1] For critiques of the reliability and predictive validity of implicit bias, see Gawronski, Morrison, Phills, and Galdi (2017) and Greenwald, Poehlman, Uhlmann, and Banaji (2009).

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. 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 model; Table D.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

The background section of this study detailed a number of factors that could potential confound a relation between aggregate rates of racial bias and black-white test score gaps. Consequently, this study controls for a set of factors that aim to capture general conditions and racial disparities in family resources and residential environments—factors that could conceivably contribute to aggregate rates of racial bias as well as to black-white test score gaps. In particular, this study captures variation in family resources by controlling for overall measures of and black-white differences in the following county-level characteristics: 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, all of which were gathered from the Stanford Education Data Archive. Additionally, this study controls for racial residential segregation, crime rates, and urbanicity, also measured at the county level, to capture variation in residential conditions. Crime rates were gathered from the FBI Uniform Crime Reporting Survey and were averaged across the 2009-2016 survey years. Urbanicity was measured as the percent of schools in the county located in census-defined urbanized areas and was gathered from the Stanford Education Data Archive. Finally, the estimates for the number of black and white residents per census tract used to compute county-level estimates of residential segregation 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 2012-16.

Of note, the inclusion of these factors also controls for any indirect effect that racial bias has on test score gaps operating through them. For instance, controlling for residential segregation also accounts for any indirect effects that aggregate rates of racial bias have on test score gaps operating through residential segregation (see Arrows 15 and 11 in Figure 1). Similarly, controlling for racial disparities in employment rates also accounts for any indirect effects that aggregate rates of racial bias have on test score gaps operating through employment disparities (see Arrows 14 and 8 in Figure 1). This point is important in light of this study's secondary aim of understanding how schools and school systems figure into how aggregate rates of racial bias materialize into educational inequality. In particular, the adjusted relation between aggregate rates of bias and test score disparities (described in more detail in the Method section) can be understood as that which arises independent not only of observable confounding but also of any indirect effects of racial bias operating through observable non-schooling factors and disparities.

Explanatory variables

As just noted, the secondary aim of this study is to understand the schooling factors that may be responsible for an observed relation between racial bias and test score disparities independent of the effects attributed to disparities in family resources and environmental conditions. This study focuses on four factors. 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. Prekindergarten disparities capture black-white gaps in prekindergarten enrollment. This variable captures the share of black and white children, respectively, in each county who were enrolled in a prekindergarten program during their respective prekindergarten year. This measure was computed by combining data on prekindergarten enrollments for each school-year cohort from the National Center for Educational Statistics' Elementary and Secondary Information System with annual enrollment counts from the Stanford Education Data Archive. 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. These years were the only surveys during the observation period for which a census of all U.S. schools was completed. 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 level between 3 and 8. Therefore, most elementary and middle schools are included in the measurement of each schooling input.

Method

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

$$\begin{aligned}
\hat{Y}_{rcs} &= \alpha_{0cs} + \alpha_{1cs}\text{Race} + e_{rcs} + \varepsilon_{rcs} \\
\alpha_{0cs} &= \beta_{00s} + \beta_{01s}\text{Bias}_{cs} + \beta_{0.s}X_{cs} + r_{0cs} \\
\alpha_{1cs} &= \beta_{10s} + \beta_{11s}\text{Bias}_{cs} + \beta_{1.s}X_{cs} + r_{1cs} \\
\beta_{00s} &= \gamma_{000} + u_{00s} \\
\beta_{01s} &= \gamma_{010} + u_{01s} \\
\beta_{10s} &= \gamma_{100} + u_{10s} \\
\beta_{11s} &= \gamma_{110} + u_{11s} \\
\beta_{0.s} &= \gamma_{0.0} \\
\beta_{1.s} &= \gamma_{1.0}
\end{aligned} \tag{1}$$

$\varepsilon_{rcs} \sim N(0, \omega^2_{rcs})$; $e_{rcs} \sim N(0, \tau^2_1)$;

$r_{cs} \sim MVN(0, \tau^2_2)$; $u_s \sim MVN(0, \tau^2_3)$

where $\hat{\gamma}_{rcs}$ 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^2_3 to be estimated; e_{rcs} is a normally distributed within-county residual with variance-covariance matrix τ^2_1 to be estimated; and ε_{rcs} is a normally distributed mean-zero error term with variance equal to ω^2_{rcs}, 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 racial 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 racial 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 racial 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 schooling-related 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 racial 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.

To model the extent to which the relation between black-white test score gaps and county-level estimates of racial 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 racial bias and racial group after the inclusion of the interaction between schooling input and racial group.

Results

Descriptive Statistics

Table 1 provides descriptive statistics for test scores by race, implicit racial bias, and all included covariates. The average achievement of black students nationwide is 0.42 standard deviation lower than the national average while the average achievement of white students nationwide is 0.11 standard deviations higher, 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 estimate of implicit bias adjusted with poststratification is 0.40, which indicates a pro-white bias on a scale in which zero equals no bias.

Figures 2 illustrates a scatterplot of the unadjusted association of academic achievement and county-level estimates of implicit bias for black versus white students.[2] The navy points refer to white students, and the grey points refer to black students. Each point in the figure 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 racial 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 that the clustering of points around each trend line is stronger for black than for white students. Indeed, the r-squared corresponding to the unadjusted relation between test scores and aggregate rates of bias for black students is 0.05

[2] For descriptive purposes, test scores in Figure 2 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).

while the corresponding r-squared values for white students is 0.02. This means that racial bias carries more signal regarding the achievement of black students than white students.

Multivariate Models

Figure 3 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 0.027 standard deviations larger ($p = .025$). This association is explained by the fact that county-level estimates of implicit bias are also associated with lower achievement for black students ($\beta = -0.033$, $p < .001$). 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 potential confounding factors, for such things as racial disparities in family resources and residential conditions, 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 0.018 ($p = .036$) standard deviations. In contrast to what was observed for the unadjusted models, however, there is no clear evidence whether the statistically significant association between county-level estimates of implicit bias and the black-white test score gap is driven by changes to the test scores of black or white students.

Figure 4 turns attention to the question of the schooling inputs that might help illuminate the association between racial bias and the black-white test score gap. In particular, Figure 4 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.[3] Reported estimates from the primary analysis are provided in the first row. Proportion explained is calculated as the percentage change in the magnitude of the interaction term after the inclusion of an interaction between racial group and the schooling input displayed in the row name.

Black-white gaps in prekindergarten enrollment and black-white funding disparities provide no predictive explanation of the association between county-level estimates of implicit bias and the black-white test score gap, while the black-white discipline gap explains 18% of the association. Far more predictive are differences in how schools sort (and label) students. Between-school racial segregation explains 31% 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 62% of the observed relation, while the entirety of the observed associations between

[3] Table C.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, give more black than white students 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, while counties with elevated rates of implicit bias against blacks have smaller disparities in prekindergarten enrollment.

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 racial 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 implicit racial bias against blacks have a black-white test score gap that is around 0.02 standard deviations larger, even after accounting for a host of observable differences and potential confounding factors 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 A.1 in the Appendix for full regression results). In other words, although the magnitudes of the relation between the black-white test score gap and county-level estimates of racial bias were substantively small, the magnitudes are 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 racial 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 racial 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 racial 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. Moreover, individuals who completed the assessment may have been more or less biased than the general population of white people in each county. Second, this study's design prevented any causal claims regarding the directional relation between racial 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 racial 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 racial bias against blacks, and by showing that this association is due to how racial 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: Directed Acyclic Graph of Theoretical Relations Between Aggregate Rates of Racial Bias and Black-White Test Score Gaps

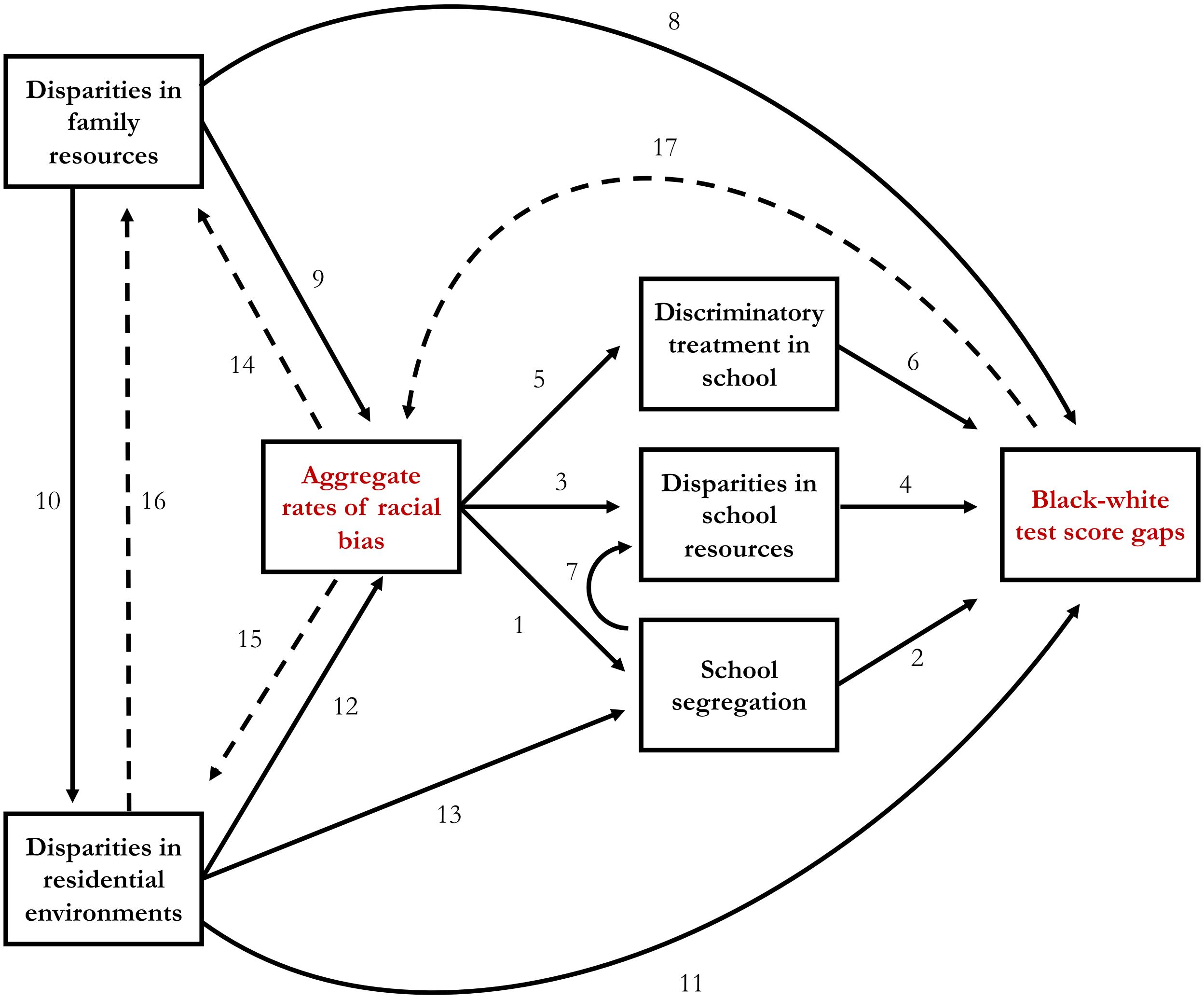

Figure 2: Scatter Plot of Achievement by Race and County-Level Estimates of Implicit Racial Bias

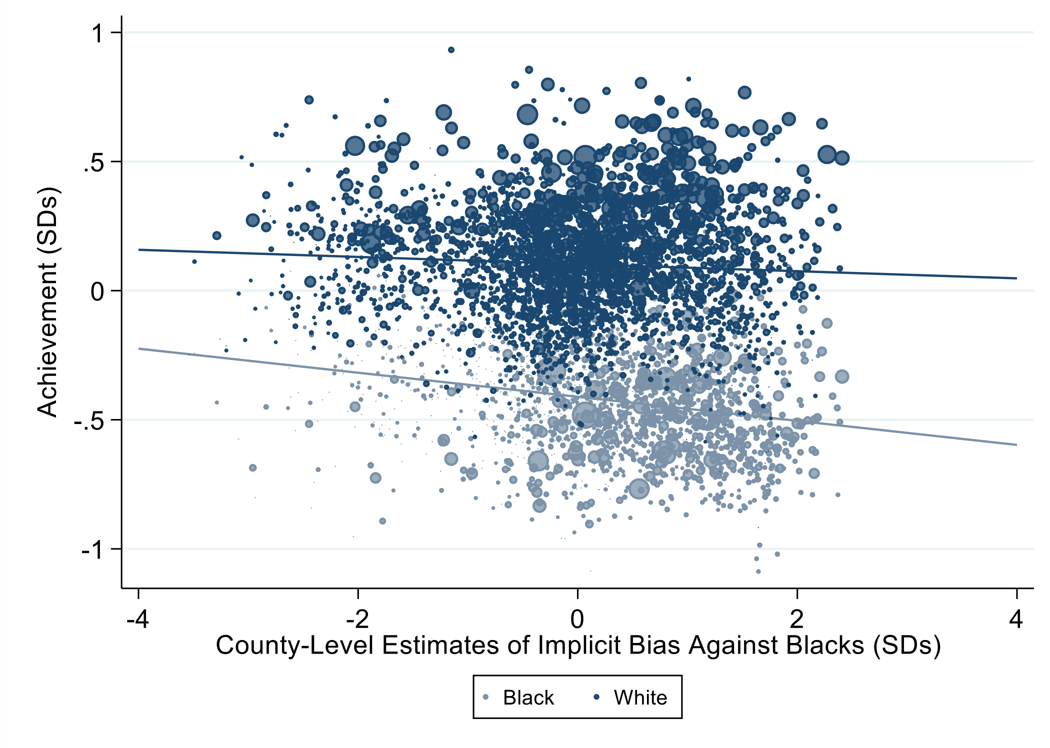

Figure 3: Unadjusted and Adjusted Relationship Between Test Scores and County-Level Estimates of Implicit Racial Bias

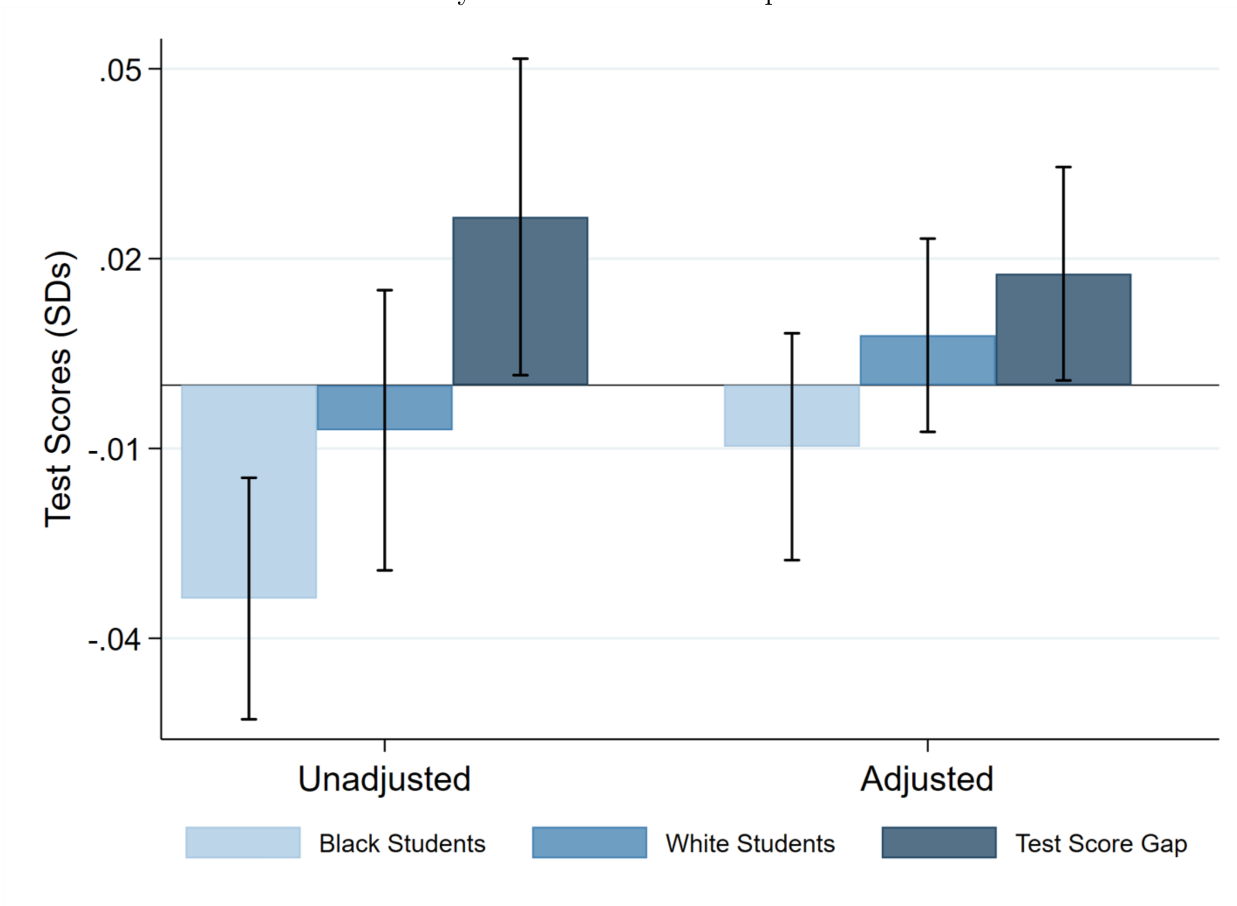

Figure 4: Adjustments to the Association Between Test Score Gaps and County-Level Estimates of Implicit Racial Bias Based on Schooling Inputs

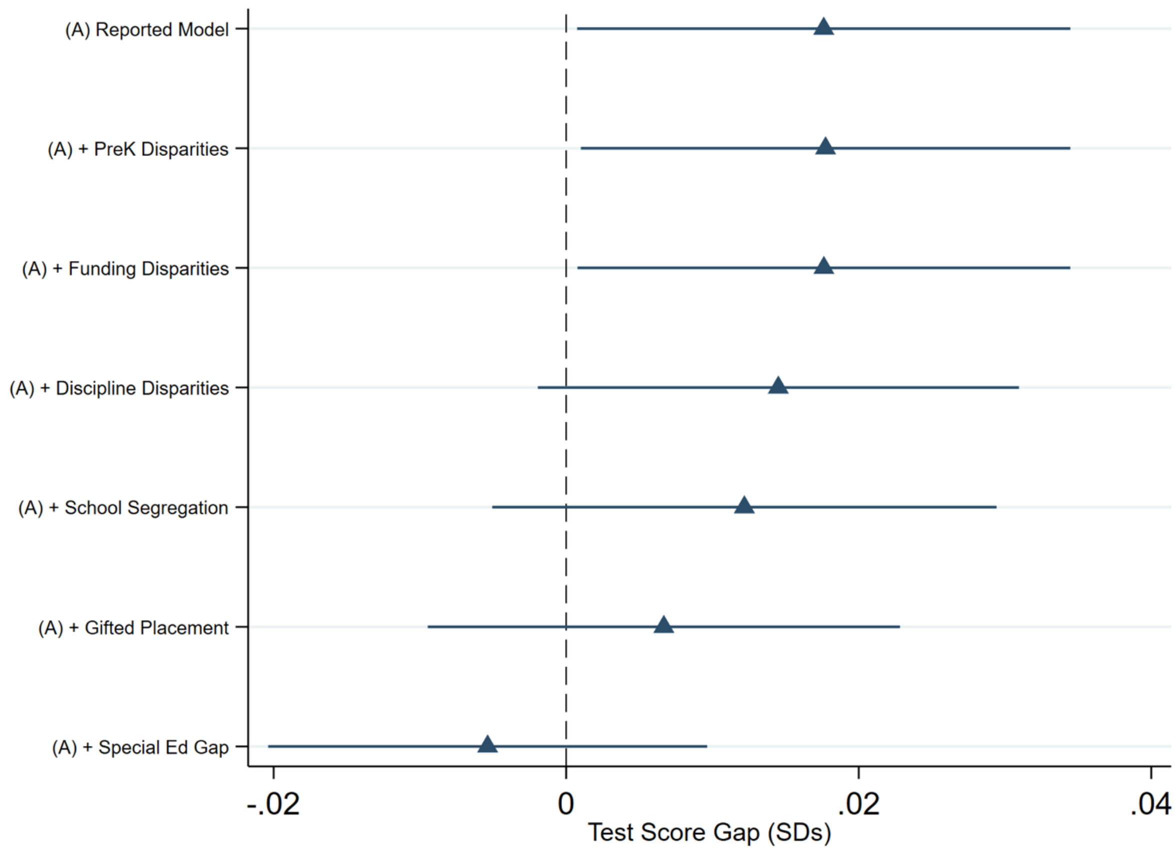

Table 1: Descriptive Statistics

	Mean	SD
Implicit Bias	0.40	0.02
Test Scores (SDs)		
Black Students	-0.42	0.21
White Students	0.11	0.22
Sociodemographic Characteristics		
% White	0.75	0.18
% Black	0.12	0.15
Total Population	139,016	372,437
% Urban	0.11	0.25
Segregation	0.10	0.12
Crime Rate (Per 100,000)	577	352
Socioeconomic Characteristics		
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
School Characteristics		
Between-School Segregation	0.14	0.12
Gifted & Talented Gap	0.04	0.04
Special Ed Gap	-0.02	0.06
Funding Gap	-495	19,150
Prekindergarten Gap	-0.03	0.16
n=	4,176	

Appendix

Table A.1: Full Results from Hierarchical Linear Regression of Academic Achievement on County-Level Estimates of Racial Bias and Other Characteristics

	Unadjusted	Adjusted
County-Level Bias	-0.034**	-0.010
	(0.009)	(0.009)
White	0.544***	0.516***
	(0.016)	(0.009)
Bias x Race	0.027*	0.018*
	(0.012)	(0.008)
<u>Sociodemographic Characteristics</u>		
% White		0.009
		(0.009)
% White x Race		-0.034***
		(0.008)
% Black		-0.007
		(0.009)
% Black x Race		-0.033***
		(0.008)
Total Pop.		0.003
		(0.004)
Total Pop. x Race		0.005
		(0.003)
% Urban		-0.007
		(0.004)
% Urban x Race		0.008*
		(0.003)
Residential Segregation		-0.020***
		(0.005)
Segregation x Race		0.040***
		(0.005)
Crime		-0.011*
		(0.005)
Crime x Race		0.014**
		(0.004)

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Table A.1: Continued

	Unadjusted	Adjusted
Socioeconomic Characteristics		
Median Income		0.029*
		(0.013)
Median Income x Race		-0.013
		(0.012)
% Bachelors or higher		0.046***
		(0.008)
% Bachelors or higher x Race		0.055***
		(0.007)
% Unemployed		-0.000
		(0.006)
% Unemployed x Race		-0.017**
		(0.006)
% SNAP		0.014
		(0.009)
% SNAP x Race		-0.027**
		(0.008)
% Poverty		0.007
		(0.011)
% Poverty x Race		-0.007
		(0.010)
% Single Mother		-0.021*
		(0.010)
% Single Mother x Race		0.008
		(0.009)
Black-White Differences		
Median Income		-0.021***
		(0.005)
Median Income x Race		0.018***
		(0.005)
% Bachelors or higher		-0.017***
		(0.005)
% Bachelors or higher x Race		0.039***
		(0.004)
% Unemployed		-0.002
		(0.004)
% Unemployed x Race		0.007
		(0.004)

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Table A.1: Continued

	Unadjusted	Adjusted
% SNAP		-0.028***
		(0.005)
% SNAP x Race		0.041***
		(0.005)
% Poverty		-0.006
		(0.005)
% Poverty x Race		0.004
		(0.005)
% Single Mother		-0.015**
		(0.005)
% Single Mother x Race		0.012**
		(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 B.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)+Pre-K Disparities (B)	(A)+Funding Disparities (C)	(A)+Discipline Gap (D)	(A)+Racial Segregation (E)	(A)+Gifted Placement Gap (F)	(A)+Special Ed Assignment Gap (G)
Bias	-0.010	-0.010	-0.010	-0.007	-0.006	-0.005	0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
White	0.516***	0.517***	0.516***	0.513***	0.518***	0.523***	0.502***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)
Bias x Race	0.018*	0.018*	0.018*	0.015	0.012	0.007	-0.005
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.007)
Pre-k		0.009					
		(0.005)					
Pre-k x Race		-0.019***					
		(0.004)					
Funding			-0.001				
			(0.003)				
Funding x Race			-0.000				
			(0.003)				
Suspensions				-0.035***			
				(0.005)			
Suspensions x Race				0.040***			
				(0.004)			

(Continued on next page)

Table B.1: Continued

	Reported (A)	(A)+Pre-K Disparities (B)	(A)+Funding Disparities (C)	(A)+Discipline Gap (D)	(A)+Racial Segregation (E)	(A)+Gifted Placement Gap (F)	(A)+Special Ed Assignment Gap (G)
Segregation					-0.035***		
					(0.005)		
Segregation x Race					0.056***		
					(0.005)		
Gifted Placement						-0.016**	
						(0.005)	
Gifted Placement x Race						0.057***	
						(0.004)	
Special Education							-0.065***
							(0.005)
Special Education x Race							0.081***
							(0.004)
n=	4,176	4,176	4,176	4,176	4,176	4,176	4,176
Proportion Explained		<1%	<1%	17.6%	30.8%	62.1%	>99%

Note: This table provides estimates of the extent to which the association between racial 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 C.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	8
1. Implicit Bias	1.00***							
2. Academic Achievement	-0.11***	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	0.40***	-0.04*	-0.01	0.33***	0.18***	0.39***	1.00***	
8. Prekindergarten Gap	-0.07***	-0.03	-0.02	-0.17***	-0.02	-0.10***	-0.17***	1.00***

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

Table D.1: Robustness Checks for Alternative Specifications of Post-Stratification Models, Alternative Measure of Racial Bias, and Disaggregated County Means of IAT Scores

	MRP w/Education & Sex REs (reported) (A)	MRP w/Age & Sex REs (B)	MRP w/ Education REs (C)	MRP w/Age REs (D)	Explicit Bias (E)	Raw Means (F)
Bias	-0.010	-0.007	-0.007	-0.006	-0.014~	-0.003
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.006)
Race	0.516***	0.516***	0.516***	0.517***	0.518***	0.513***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
Bias x Race	0.018*	0.021*	0.021*	0.022*	0.019**	0.013~
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
n=	4,176	4,176	4,176	4,176	4,176	4,176

Note: All models are fully adjusted. 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. Explicit bias (Column F) is measured as the difference in respondents' reported warmth toward white versus black people. Raw county means (Column F) are unstandardized disaggregated county averages of implicit bias scores without accounting for demographic or geographical variation. Standard errors are in parenthesis. ~p<.10, *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