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Racial Bias and Opportunity Gaps: When and How Bias Affects Disparities in the Advanced Placement Participation

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RACIAL BIAS AND OPPORTUNITY GAPS: WHEN AND HOW BIAS AFFECTS DISPARITIES IN THE ADVANCED PLACEMENT PARTICIPATION

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Abstract

Opportunities to develop and demonstrate academic potential and excellence are often unequally distributed across racial groups, exacerbating disparities later in life. This dissertation seeks to understand the role of racial bias in shaping these "opportunity gaps." In the first chapter, I examine whether county-level pro-White/anti-Black implicit and explicit biases are associated with Black-White disparities in AP program participation. I find that greater disparities in AP course enrollment are observed in counties where White residents exhibit higher levels of bias; this relationship is, in part, explained by an interpersonal route (i.e., White teachers in these counties also exhibit higher levels of bias themselves). The second chapter builds on this finding by testing whether White teachers' implicit and explicit biases predict differential evaluations of Black and White students applying for AP courses. Two experimental studies do not support this hypothesis, highlighting the need for future research on whether and when teachers' biases affect enrollment disparities. In the final chapter, I examine whether the very nature of opportunities like AP—valuable and scarce—amplifies the link between implicit bias and disproportionate outcomes. I show that White individuals' implicit bias predicts worse placement outcomes for Black students only when opportunities are described as both valuable and scarce, but not when either attribute is absent. Together, this dissertation advances research on racial excellence and opportunity gaps by providing insights into when and how racial bias contributes to these disparities.

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Introduction

One opportunity often leads to another. Students placed in gifted and talented programs are more likely to enroll in advanced courses such as honors or Advanced Placement (AP) later in their academic careers (Bhatt, 2009). These courses, in turn, strengthen college applications by signaling one's academic ability and college readiness (Naff et al., 2021). Getting a college education—especially from a highly selective institution—further increases the likelihood of pursuing graduate education (Zhang, 2005) and becoming the top 1% of earners (Chetty et al., 2020). Given the additive nature of opportunity, addressing persistent racial disparities in educational attainment and economic mobility requires examining whether opportunities to develop and demonstrate one's potential are equitably distributed across racial groups.

Research consistently shows that opportunity gaps exist at every stage. Low-income and minority students are substantially underrepresented in gifted and talented programs (Long et al., 2023), honors and AP courses (Corra et al., 2011), and degree-granting colleges, especially more selective institutions (Baker et al., 2018). As complex social phenomena, these disparities are multiply determined; for example, intergenerational mobility and parental networks shape access to educational opportunities (Chetty et al., 2020; Hamilton et al., 2018), and residential segregation could determine the quality of schooling and resources available (Baker et al., 2018). Beyond these structural barriers, this dissertation argues that *racial bias in students' broader social environments* also contributes to the unequal distribution of opportunities. Chapter 1 explores the relationship between regional bias and racial disparities in AP participation across three stages (course enrollment, exam taking, and exam passing). Chapter 2 investigates the role of teachers' biases in shaping AP placement decisions. Finally, Chapter 3 identifies the types of opportunities for which implicit bias is most likely to influence race-based evaluations of

students. Before turning to the research, the following sections provide an overview of the AP program—a paradigmatic example of an opportunity that unlocks future ones—as well as a review of implicit bias and its role in shaping racial disparities.

The AP Program: Background

The AP program was launched in 1955 in response to the growing consensus that high-achieving students should have access to more challenging coursework earlier, facilitating a smoother transition to postsecondary education (Finn & Scanlan, 2019). Created and administered by the College Board, a private nonprofit organization, the program offers college-level courses across various disciplines that students can take while still in high school. Schools wishing to offer AP courses must submit a course plan or syllabus to the College Board for approval, ensuring that curricula meet college-level criteria. At the end of the academic year, students may choose to take AP exams—standardized assessments created and scored by teams of AP teachers and college faculty—that evaluate their mastery of subject-specific content and skills. A qualifying score (typically 3 or above on a 1-5 scale) can subsequently be used for college credits at participating institutions.

Over the years, the AP program has become the nation's most prominent college preparatory program. In the 2020-21 academic year alone, more than 2.5 million students took 4.5 million AP exams, with over 3,000 colleges accepting qualifying scores for credits (College Board, 2021). While other programs such as dual enrollment also allow high school students to experience college-level coursework, AP stands out for its *standardized nature*—with both curricula and exams designed and administered by the College Board, ensuring consistency in students' experiences and the interpretation of their performance (Kolluri, 2018).

The benefits of participating in the AP program extend from high school to college admissions and beyond. Students in AP courses often learn from more experienced teachers and report a richer learning experience, describing AP courses as challenging yet intellectually stimulating environments where critical thinking is encouraged, unlike "boring" regular classes in which students "don't do much thinking" (Hertberg-Davis & Callahan, 2008, p. 200). Having AP courses on a transcript also sends a positive signal to admissions officers, demonstrating a student's willingness to take on academic challenges (Geiser & Santelices, 2004). Additionally, performance in AP courses and exams offers a reliable metric of academic accomplishment, which is particularly valuable for evaluating applicants from historically underrepresented backgrounds who attend high schools in remote areas where the rigor and quality of instruction are relatively less known to admission officers (Finn & Scanlan, 2019). Beyond college admissions, performance on AP exams (but not course enrollment alone) is associated with stronger college performance (Hargrove et al., 2008). Students who earn qualifying scores can also use their AP credits to bypass introductory courses, accelerating graduation or enrolling in more advanced coursework to improve their post-graduation outcomes (Evans, 2019). Altogether, by challenging students academically, exposing them to rigorous learning environments, and potentially allowing them to accelerate in college, AP serves as an early opportunity that can shape students' long-term academic trajectories. Recognizing these benefits, federal and state governments have identified the AP program as a key strategy for expanding college readiness and helping students in underserved communities transition more smoothly into postsecondary education (Finn & Scanlan, 2019). Substantial efforts and resources have been invested in expanding the program, particularly in schools serving low-income and racial

minority students (Kolluri, 2018), such as New York City's AP for All initiative which aimed to have every high school in the city offer at least five AP courses.

Despite these expansion efforts, racial disparities in AP participation persist across all stages. Even after accounting for socioeconomic status, racial segregation, and prior academic achievement, White students are 1.3 times more likely to take AP courses than Black students (Shores et al., 2020). Another study projects that if access to AP courses were equitable, nearly 158,000 additional Black students would be enrolled in AP classrooms annually (Patrick et al., 2020). These differences exist both between and within schools. Black students are overrepresented in schools with limited AP offerings and underrepresented in schools with greater offerings, while White students are evenly distributed and Asian students overrepresented in schools with greater offerings (Chatterji et al., 2021). Within schools, Black students remain underrepresented in AP courses, and White and Asian students overrepresented (Siegel-Hawley et al., 2021). Beyond enrollment, Black students are also less likely to succeed on AP exams; even in schools with the highest levels of AP access (offering 18 or more AP courses), the rate of Black students passing at least one AP exam is 30 percentage points lower than that of White students (Chatterji et al., 2021). These disparities underscore the need to understand their basis, particularly the role that racial biases may play in shaping enrollment and performance in advanced courses.

Measuring Racial Bias and Its Role in Real-World Disparities

Racial bias is typically measured in two ways, explicitly and implicitly (Blair et al., 2015). Explicit bias refers to consciously held and endorsed attitudes, typically assessed through self-report surveys asking how people feel about certain social groups. Implicit bias, on the other hand, captures relatively less conscious associations between groups and evaluative concepts. It

is often measured using reaction time tasks such as the Implicit Associations Test (IAT), which infers the strength of automatic associations—such as White/positive and Black/negative pairings—by analyzing response latencies. Research indicates that pro-White/anti-Black bias persists in both forms, though implicit bias is more prevalent. For example, data from Project Implicit (2007-2020) indicate that 29% of respondents reported explicit preferences for White over Black people, and 65% exhibited implicit preferences (Morehouse & Banaji, 2024).

Importantly, both forms of biases have been shown to predict intergroup behavior. A recent meta-analysis of 217 research reports encompassing more than 36,000 participants found that implicit ($\beta = 0.14$) and explicit ($\beta = 0.11$) measures[1] predict intergroup behavior to a comparable extent, even after accounting for each other's influence (Kurdi et al., 2019). Although the majority of studies in this meta-analysis were lab-based and primarily involved undergraduate students, similar effect sizes were observed in field studies and those with online participants, suggesting that the predictive validity of bias measures is robust enough to be observed even in less controlled, real-world settings.

A small but growing body of research on regional intergroup bias, facilitated by advances in large-scale online data collection, provides further support. Implicit and explicit racial biases are more strongly correlated at the regional level than at the individual level (potentially due to reduced measurement error and shared cultural influences), making it harder to disentangle the contribution of one over the other. Nonetheless, pro-White/anti-Black implicit and explicit regional bias have been found to be associated with Black-White disparities in numerous domains, including healthcare access (Leitner et al., 2016), death rates from circulatory diseases

[1] These meta-analytic correlations were obtained across different concepts (attitudes, stereotypes, identity). When considering only implicit and explicit *attitudes*, the correlation with the criterion behavior was 0.10 and 0.15 for implicit and explicit attitudes, respectively.

(Leitner et al., 2016), police traffic stops (Ekstrom et al., 2022), use of lethal force (Hehman et al., 2018), and school disciplinary actions (Chin et al., 2020; Riddle & Sinclair, 2019). Of particular relevance to this dissertation, regional implicit and explicit bias have also been shown to be associated with greater disparities in access to Gifted and Talented programs (Pearman & McGee, 2022)—an important example of advanced learning opportunities within the US education system. However, important questions remain. Are some disparities *unrelated* to regional bias, and if so, why? When regional bias is linked to certain disparities, such as AP course enrollment, *through what mechanisms* does it operate? Regional bias reflects the collective biases of many individuals, but *whose* bias matters most in shaping these outcomes? Moreover, are there *specific contexts* that amplify the influence of individual biases—a question that has garnered particular interest in the implicit bias literature (Gawronski, 2019)—thereby leading to differential educational opportunities afforded to Black and White students?

This dissertation aims to shed light on these questions by examining how regional and individual biases contribute to racial disparities in advanced educational opportunities. Chapter 1 demonstrates that county-level pro-White/anti-Black bias is associated with greater Black-White disparities in AP course enrollment, but this pattern does not hold for disparities in exam taking and passing. It further shows that the relationship between regional bias and enrollment disparities is partially driven by teachers' biases, suggesting that their biases may shape how they perceive and interact with students of different races, ultimately contributing to disparate enrollment outcomes. Chapter 2 builds on this finding by examining whether teachers with stronger biases rely more on racial cues when making AP placement decisions. Finally, Chapter 3 explores competition for highly valuable and scarce opportunities as a key context in which implicit bias is most likely to shape race-based evaluations of students. Together, this dissertation

provides a more nuanced understanding of if and when racial bias contributes to disparities in advanced educational opportunities—insights critical for informing policies and interventions aimed at reducing educational inequities.

Chapter 1: County-level Racial Bias and Disparities in AP Participation

A great deal of research and public discourse on racial achievement gaps focuses on disparities in punitive experiences (Gregory et al., 2010; Okonofua et al., 2016) or academic attainment at basic and proficient levels (e.g., as highlighted by the No Child Left Behind Act). Relatively less attention has been given to racial excellence gaps, or disparities in achievements at the highest levels (Plucker et al., 2010). These gaps stem partly from unequal rates of participation in opportunities to develop and demonstrate excellence, such as gifted education (Plucker & Peters, 2020), advanced coursework (Patrick et al., 2020), and enriching extracurricular activities (Park et al., 2024). Understanding the basis of these gaps—not only in achieving excellence, but also in simply having the opportunity to achieve it—is critical, as excelling in these opportunities plays a central role in applications to highly selective and elite colleges, which further pave the way for students to pursue advanced degrees and be among the top 1% of earners (Chetty et al., 2020; Zhang, 2005).

The present research examines how *racial bias* relates to disparities in Advanced Placement (AP) program participation, a paradigmatic example of an opportunity to demonstrate excellence within the US education system. Designed and administered by the College Board, the AP program offers students opportunities to take college-level courses while in high school. Students in AP courses often learn from more experienced teachers (Hertberg-Davis & Callahan, 2008), may earn a boost in GPAs (as AP courses often carry extra grade points; Klopfenstein & Lively, 2016), and are perceived as more academically ambitious in college admissions (Finn & Scanlan, 2019). Students can further choose to take AP exams at the end of the academic year; qualifying scores on these exams can grant college credits, which students can use to accelerate college graduation or take advanced courses to improve post-graduation outcomes (Evans,

2019). Despite its popularity, with millions of high school students taking AP courses and exams each year (College Board, 2021), Black students remain disproportionately underrepresented in the program. One study projects that equitable access to AP courses would add nearly 158,000 Black students to AP classrooms annually (Patrick et al., 2020). Addressing if and how racial bias contributes to these disparities is especially important in the current college admissions landscape, where institutions increasingly rely on GPAs and qualitative indicators of academic ambition in lieu of test scores, and are legally prohibited from directly considering race to mitigate potential bias (Leonhardt, 2024; Liptak, 2023).

Extant research has identified multiple routes through which racial bias may contribute to disparities in achieving excellence or participating in opportunities to do so, though often indirectly. For example, research on stereotype threat suggests that concerns about bias can dissuade stigmatized students from pursuing challenging opportunities (Woodcock et al., 2012) and impede their performance when they do (Walton & Spencer, 2009), but these studies largely focus on students' perceptions of bias rather than directly measuring the presence of bias in the academic environment. Qualitative and quantitative research on systemic racism and opportunity hoarding offers externally valid accounts of institutional practices that disproportionately channel opportunities to advantaged groups—such as racial disparities in school funding (Morgan, 2022) or exclusionary selection criteria (Sattin-Bajaj & Roda, 2020)—yet they also often do not directly assess the extent to which bias is present in the broader environment. Emerging work on teacher bias has taken a more direct approach by measuring educators' biases and demonstrating that greater bias is associated with greater disparities in academic performance (Chin et al., 2020; van den Bergh et al., 2010) and representation in advanced opportunities (Carlana et al., 2022).

The present work builds on existing research on bias and opportunity gaps, examining whether pro-White/anti-Black implicit and explicit biases in the broader environment (county) are related to Black-White disparities in AP participation among US public high school students, using data from Project Implicit and the Civil Rights Data Collection (CRDC). Using regional bias allows us to capture both the biases of individuals who directly interact with students and biases embedded in local institutional practices (Ekstrom et al., 2022), both of which can shape student outcomes. As a preview of the results, we[2] found that disparities in AP *course enrollment* were larger in counties where residents held more negative attitudes toward Black people. This was not the case for *exam taking or passing*, potentially suggesting that racial bias primarily influences the initial selection process—that is, who gets the opportunity to participate in the AP program, rather than who excels once enrolled. We then subsequently examined three potential ways—structural, developmental, and interpersonal—that county-level bias may shape AP course enrollment disparities.

Results

Analyses were first conducted on data from 2013-14 academic year and preregistered for later years (2015-16, 2017-18[3]). Table 1.1 presents Black and White students' participation rates at each stage of AP program at each academic year.

[2] Work from Chapter 1 was conducted in collaboration with Stacey Sinclair and Travis Riddle. Work from Chapters 2 and 3 were conducted in collaboration with Stacey Sinclair.

[3] The two most recent datasets (2020-21, 2021-22) only include information about the number of students enrolled in at least one AP course. Because data on two key outcomes (exam taking and passing) were not collected, we did not analyze these years.

Table 1.1. Percentage of Black and White students participating in the AP program.

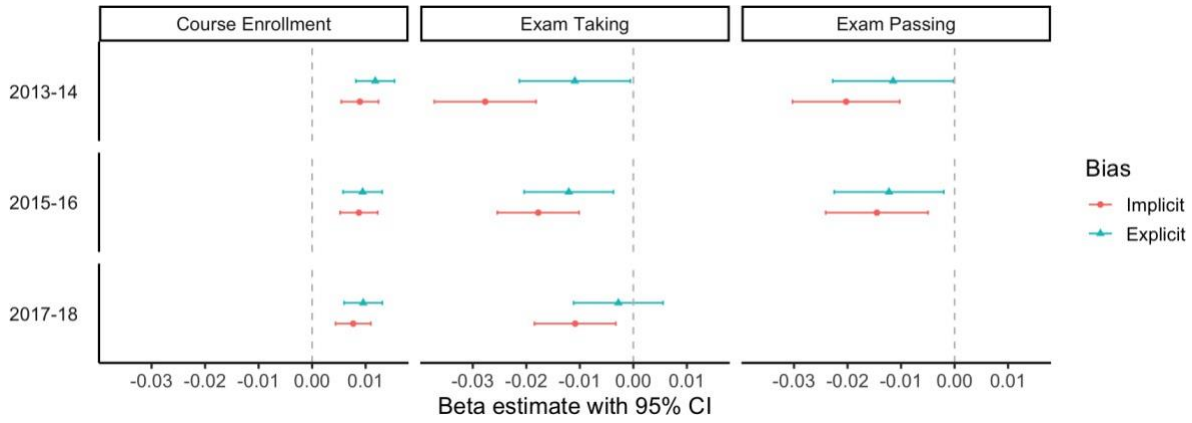
	2013-14		2015-16		2017-18	
	Black	White	Black	White	Black	White
AP Course Enrollment	12.0%	23.1%	13.2%	24.7%	14.2%	26.3%
AP Exam Taking	66.5%	72.2%	68.4%	76.7%	67.8%	77.4%
AP Exam Passing	37.4%	66.0%	38.9%	66.8%	-	-

Note. For calculating AP course enrollment rates, grades 9-12 Black or White enrollment (corrected using the Common Core Data) was used as a denominator; for AP exam taking, the number of Black or White students who were enrolled in least one AP course; and for AP exam passing, the number of Black or White students who took at least one AP exam. Schools with denominators smaller than 10 were excluded from these calculations and subsequent analyses. Data on the number of students who passed at least one AP exam was not collected in 2017-18. Differences in Black-White participation rates were significant across all metrics and years (ps < 0.001).

Is Regional Racial Bias Associated with AP Participation Gaps?

We examined whether greater Black-White gaps in AP participation are observed in counties with higher levels of racial bias. Specifically, for each stage of the program (course enrollment, exam taking, exam passing) and type of bias (implicit or explicit), we ran a multilevel regression modeling Black-White participation gaps as a function of county-level bias. The regression also included various county-level covariates, such as population size, socioeconomic indicators, and segregation (see *Materials and Methods* for a full list), as well as random intercepts by counties to account for baseline differences in participation gaps, and all predictors were standardized to improve estimation efficiency and interpretability. The results of these analyses are presented in Figure 1.1. If the main effect of bias was significant, we conducted follow-up analyses by running two separate models: one with Black students' participation rates as the outcome and the other with White students' participation rates as the outcome. This allowed us to examine whether bias was primarily associated with lower participation among Black students or higher participation among White students.

Figure 1.1. Multilevel regression results modeling Black-White AP participation gaps. County-level implicit and explicit bias are consistently associated with greater course enrollment gaps (left) but generally associated with smaller gaps in exam taking (middle) and passing (right).



Note. Error bars represent 95% confidence intervals. See *Appendix A* for full regression results, including county-level covariates.

We initially preregistered multilevel binomial regressions, modeling the likelihood of participating in the AP program as a function of county-level bias, student race, and their interaction. We deviated from this approach in favor of the current model for interpretability and consistency with the mediation analysis. The results from binomial regressions, reported in *Appendix A*, were largely consistent with those reported in the main text.[4]

Course Enrollment

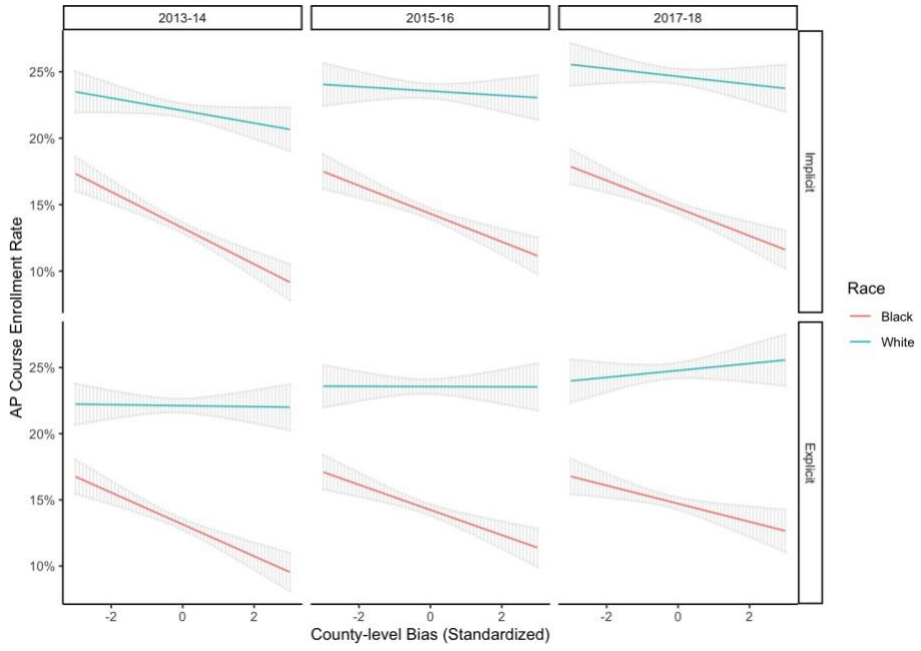
Consistent with prior literature suggesting that bias plays a role in educational disparities, county-level implicit bias was associated with greater Black-White gaps in AP course enrollment across all three years ($ps < 0.001$), even after controlling for various county characteristics. In 2017-18, moving from a low-biased county (1 SD below the mean level of

[4] The only notable difference was that implicit and explicit bias were generally not associated with Black-White differences in the likelihood of taking and passing AP exams (unlike in the main analyses, where both types of bias were associated with smaller gaps in exam taking and passing). Nonetheless, both analyses lead to the same conclusion: Bias plays a critical role in shaping disproportionate outcomes at the earliest stage of the AP program, i.e., the selection process.

implicit bias) to a high-biased county (1 SD above the mean), while holding other variables constant, was associated with a 1.5 percentage point increase in the Black-White enrollment gap. This effect is comparable in magnitude to the impact of an analogous (i.e., 2 SD) shift in the Black-White college graduation gap. Examining racial groups separately, greater implicit bias was associated with lower enrollment rates for Black students, but did not affect White students' enrollment rates (Figure 1.2, top panel).

County-level explicit bias was also associated with greater Black-White gaps in AP course enrollment across all three years (*p*s < 0.001), again driven by greater explicit bias associated with lower enrollment rates for Black students, but not White students (Figure 1.2, bottom panel). In 2017-18, moving from a low-biased to a high-biased county was associated with a 1.9 percentage point increase in the Black-White enrollment gap.

Figure 1.2. County-level implicit (top) and explicit (bottom) bias are consistently associated with lower AP course enrollment rates for Black students, but not White students.



Note. Regression lines and 95% confidence intervals were obtained from multilevel regressions modeling course enrollment rates for either Black or White students as an outcome. See *Appendix A* for parallel figures for AP exam taking and passing rates.

Exam Taking and Passing

In contrast to the AP course enrollment findings, county-level implicit bias was associated with *smaller* Black-White gaps in AP exam taking (ps < 0.005) and passing (ps < 0.003) across all years. For exam taking, implicit bias was associated with higher participation rates for both Black and White students, but the regression coefficients were larger and more consistently significant for Black students. For exam passing, the results were less clear, with no consistent evidence indicating whether implicit bias was primarily associated with passing rates for Black or White students.

Similarly, county-level explicit bias was also associated with smaller Black-White gaps in AP exam taking (ps < 0.039) and passing (ps < 0.046), except for exam taking gaps in 2017-18 (p = 0.510). For both exam taking and passing, there was no clear evidence whether explicit bias was primarily associated with Black or White students' outcomes.

Do Structural, Developmental, and/or Interpersonal Mediators Explain the Relationship between Regional Racial Bias and AP Enrollment Gaps?

Thus far, we have found that county-level bias was associated with greater Black-White gaps in AP course enrollment but smaller gaps in subsequent exam taking and passing, suggesting that bias plays a critical exclusionary role at the point of *selection*. We next conducted mediation analyses to compare three plausible pathways, identified in prior literature, through which county-level bias may exert its influence on enrollment outcomes.

The *structural* pathway posits that bias shapes enrollment disparities through differences in AP courses availability across local schools. Extant research documents racial differences in the odds of attending high-quality schools (Owens, 2020). In the context of AP courses, Black students are less likely than White students to attend schools with comprehensive AP programs

(i.e., offering at least one course each in English, Math, Science, and Social Sciences; Theokas & Saaris, 2013), although this gap has narrowed over time (Patrick et al., 2020). Nevertheless, if Black-White disparities in AP course offerings are more pronounced in regions where people are more biased against Black people, Black students in these areas may face particularly limited opportunities to enroll in AP courses. While no research has directly examined this link, increases in racial segregation—a structural feature associated with regional bias (Stier et al., 2024)—have been found to be associated with larger disparities in school resources (Sosina & Weathers, 2019), providing preliminary evidence that disparities in access to resource-intensive curricula, like AP, may be especially severe in more biased areas.

The *developmental* pathway suggests that bias shapes enrollment disparities through racial differences in academic achievement prior to high school. Extant research has documented persistent racial gaps in school grades and test performance, with Black students lagging behind White students as early as kindergarten (Reardon & Portilla, 2016). These gaps persist or even widen over time (Fryer & Levitt, 2006) and can directly impact AP enrollment outcomes, as schools often consider factors like GPAs and prerequisites to determine readiness for AP coursework (Naff et al., 2021). Subsequently, if early academic disparities are more pronounced in biased regions, Black students in these areas may be relatively less qualified to enroll in AP courses. Recent work supports this possibility, showing that teachers' racial bias was associated with poorer performance of stigmatized minority students in early education (Peterson et al., 2016; van den Bergh et al., 2010), and regional bias associated with greater disparities in participation in Gifted and Talented programs (Pearman & McGee, 2022).

Finally, the *interpersonal* pathway asserts that bias shapes enrollment disparities through interactions between students and biased individuals. In particular, we focus on teachers, who

can directly or indirectly influence students' enrollment outcomes. Teachers make fewer positive referrals for Black students than for White students (Tenenbaum & Ruck, 2007) and respond more favorably to requests from White parents to place their children in advanced tracks (Lewis & Diamond, 2015). Importantly, racial differences in expectations (Gershenson & Papageorge, 2018), referrals (Grissom & Redding, 2016), and enrollment in advanced programs (Hart, 2020) are more pronounced among White teachers than Black teachers, suggesting that teachers' racial bias may exacerbate these disparities. Recent evidence affirms that more implicitly biased teachers recommended immigrant students more often to vocational tracks and less often to top-tier academic tracks (Carlana et al., 2022). Similarly, counties with higher levels of teacher implicit and explicit bias exhibited greater Black-White disparities in standardized test scores and suspension rates (Chin et al., 2020).

We ran a mediation model to assess which of the three pathways explain the relationship between overall bias and AP enrollment gaps. All mediators were constructed at county-level. For the *structural* mediator, we computed the correlation between the number of AP courses offered and the representation of White over Black students across schools within each county. Positive values indicate that predominantly White schools offer more AP courses, reflecting greater disparities in AP availability. For the *developmental* mediator, we used Black-White achievement gaps on standardized tests in math and reading administered prior to high school. For the *interpersonal* mediator, we estimated implicit and explicit racial bias using responses from White teachers in the Project Implicit dataset. See *Materials and Methods* for more details on how each mediator was operationalized.

To ensure valid comparisons of the explanatory value of the mediators, we included only counties with all three mediators available. The mediation model included the direct effect of

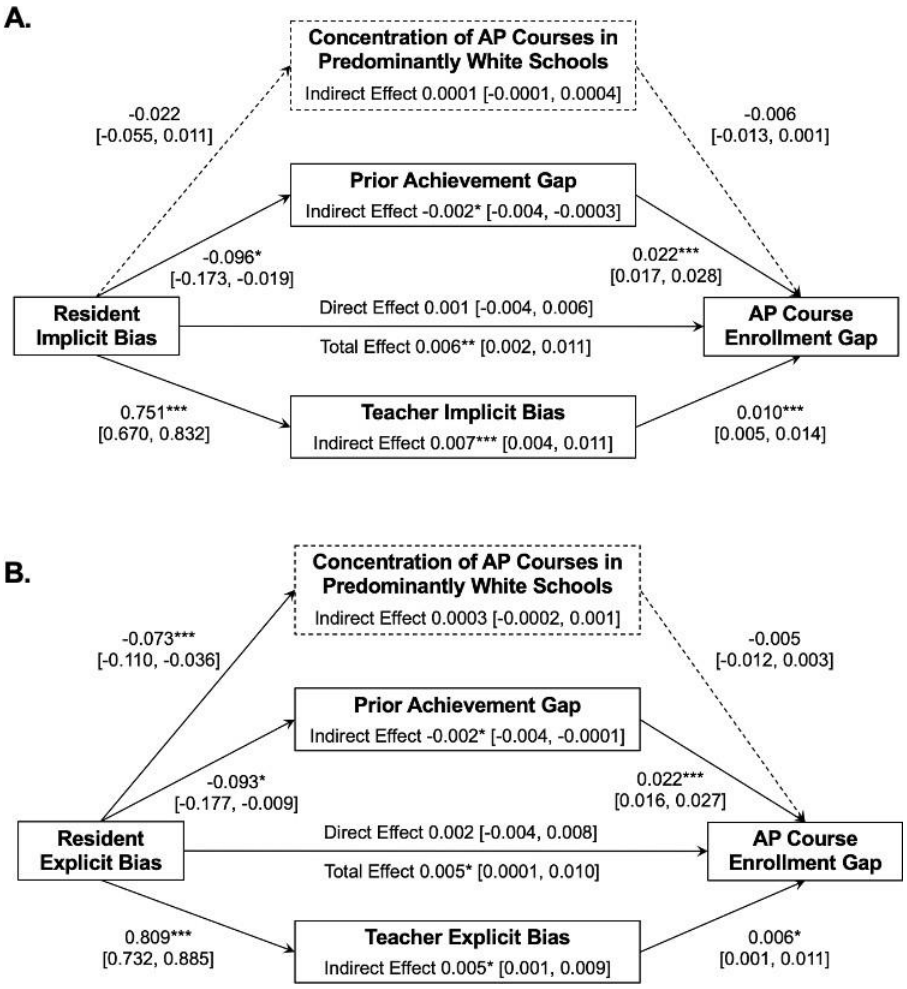
county-level bias on enrollment gaps and indirect effects through all three mediators, with covariates controlled in all paths (see *Appendix A* for parallel analyses for exam taking and passing gaps). For socioeconomic covariates (unemployment rate, median income, poverty rate, college graduation rate), to avoid multicollinearity, we used principal component analysis and extracted the first principal component as a composite SES measure; the same procedure was applied to Black-White SES differences.[5] Maximum likelihood estimation with robust standard errors was used to account for clustering by county.

Across all six cases (three years and two types of bias), the interpersonal mediator consistently emerged as statistically significant. In contrast, the structural mediator emerged as statistically significant in only one out of six cases, and the developmental mediator emerged as significant in four out of six cases, but in an unexpected direction (for similar findings, see Chin et al., 2020). For example, in 2017-18, regional implicit bias was positively associated with teachers' implicit bias, which in turn was associated with greater enrollment gaps, resulting in a significant indirect effect via the interpersonal pathway (ps < 0.001). In contrast, regional implicit bias was not associated with the concentration of AP courses in predominantly White schools (p = 0.195), and this concentration was also not associated with enrollment gaps (p = 0.117), yielding a non-significant indirect effect (p = 0.300). Lastly, regional implicit bias was associated with smaller achievement gaps prior to high school (p = 0.014), which was associated with smaller enrollment gaps (p < 0.001), yielding a significant indirect effect for the developmental pathway (p = 0.019; Figure 1.3A) but in the opposite direction of what the

[5] We initially preregistered to model SES and SES difference as latent constructs, but this approach yielded poor fit indices. Inspection of modification indices suggested adding residual covariances between indicator variables used to define SES and SES differences, but adding these residual covariances led to estimation errors such as negative variance estimates. As such, we switched to employing principal component analysis to create composite SES variables, which mitigates multicollinearity while preserving shared variance, and used the first principal component (PC1) as an observed variable in the mediation model.

literature may have predicted—namely, that bias would be associated with greater prior achievement gaps, explaining greater enrollment gaps. Results were largely similar for explicit bias (Figure 1.3B). See *Appendix A* for full results for earlier years.

Figure 1.3. Mediation analysis of the relationship between resident implicit bias (A) or explicit bias (B) and AP course enrollment gaps.



Note. Path diagram with regression coefficients and confidence intervals from the mediation analysis of the relationship between resident implicit bias (A) or explicit bias (B) and the AP course enrollment gap. Dotted lines represent non-significant relationships ($p > 0.05$).
†$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Robustness Checks

To test the robustness of the results, we conducted two checks. First, to address concerns about the reliability of teacher bias estimates, we re-ran the mediation analysis using progressively smaller sets of counties, where teacher bias estimates were based on larger teacher samples (at least 30, 50, and 100 teachers who completed the Project Implicit survey, instead of 10). For implicit bias, the interpersonal mediator continued to remain significant in the hypothesized direction (regional implicit bias positively associated with teachers' implicit bias, which in turn was associated with greater enrollment gaps). Interestingly, for explicit bias, the indirect effect of the interpersonal mediator was no longer significant in 2015-16 and 2017-18 when using these smaller samples (see *Appendix A* for full statistics).

Second, to address the possibility that the significant indirect effect of teachers' bias was driven solely by methodological overlap in the measurement of regional and teachers' bias, we replaced teachers' racial bias with teachers' *sexuality* bias (pro-straight/anti-gay bias) and tested whether it also emerged as a significant mediator (see Riddle & Sinclair, 2019 for a similar approach). Across all three years and both types of bias, teacher sexuality bias was not a significant mediator. While regional racial bias was significantly associated with teachers' sexuality bias (ps < 0.001, though less strongly than with teachers' racial bias), teachers' sexuality bias was not significantly associated with racial enrollment gaps—suggesting that teachers' racial bias shapes unique, race-based interpersonal dynamics influencing enrollment outcomes for Black versus White students.

Discussion

The present research examined the relationship between racial bias and AP participation across US public high schools. County-level pro-White/anti-Black bias was consistently

associated with greater Black-White disparities in AP course enrollment, but this pattern did not hold for exam taking or passing. The relationship between bias and enrollment gaps was explained through an interpersonal pathway: Teachers in more biased counties exhibited stronger bias themselves, which in turn was associated with greater enrollment gaps. Structural and developmental factors previously identified as determinants of AP course enrollment—disparities in course availability and prior achievement gaps—did not explain this relationship.

One potential explanation for these findings is that the threshold for Black students to enroll in AP courses may be higher in more biased counties. Prior research suggests multiple ways this could occur. Biased teachers may directly influence enrollment by referring White over Black students to advanced courses (Tenenbaum & Ruck, 2007), responding differently to Black versus White parents' requests to override placement decisions (Lewis & Diamond, 2015), or failing to foster a sense of belonging in AP classrooms, discouraging Black students from enrolling (Taliaferro & DeCuir-Gunby, 2008). These barriers may operate independently of students' prior performance, as demonstrated by experimental studies showing that disparate outcomes can arise even when students are equally qualified (Francis et al., 2019). Put differently, even if Black students in more biased regions perform well, interpersonal biases may continue to limit their participation in AP coursework, increasing enrollment gaps in these regions.

Our findings help explain a paradox highlighted by recent research that AP enrollment disparities are larger in schools offering more AP courses (Chatterji et al., 2021) or in states with policies expanding AP access (Xu et al., 2021). Even in these contexts, interpersonal processes—such as differential gatekeeping, parental interference, and student interest—may continue to shape who ends up in AP classrooms. However, these findings should not be interpreted as

evidence against expanding AP access. Limited AP offerings remain a key driver of enrollment disparities beyond racial bias, and while increasing access alone would not eliminate the effects of racial bias, it would still help reduce disparities in the affordability and availability of AP opportunities. Additionally, our mediation analyses focused on schools in counties with at least three AP-offering schools (see *Materials and Methods* for details); these schools tended to be larger than schools not included, potentially introducing selection bias. One possibility that warrants further investigation is that larger schools may have more complex selection processes (e.g., teacher recommendations), creating greater opportunities for interpersonal biases to shape AP enrollment. If so, the influence of the interpersonal mediator may be more pronounced than in smaller schools, where selection processes may be less restrictive.

This study opens multiple avenues for future research. First, the effects described here are correlational, precluding causal claims. It is possible that the underrepresentation of Black students in AP classrooms shapes teachers' biases. Nevertheless, our externally valid findings align with experimental research showing that teachers perceive equally-qualified Black and White students differently (Francis et al., 2019), together suggesting that teacher bias can influence student outcomes. Future work may explore particular conditions (e.g., school or district policies; Card & Giuliano, 2016) under which teacher bias is most likely to produce disproportionate outcomes. Future research may also explore whether the relationship between racial bias and AP enrollment disparities extends to other underrepresented groups.

Overall, the present study demonstrates that racial bias contributes to racial disparities in the nation's leading college preparatory program. While the AP program holds the potential to expand access to higher education, this promise remains unfulfilled if interpersonal biases prevent Black students from participating in these courses. Expanding AP offerings to schools

that primarily serve underrepresented students is a valuable endeavor, but reducing the influence of interpersonal bias in AP enrollment at schools that already offer the program (e.g., automatic enrollment for qualified students; Austin et al., 2025) may be a more cost-effective way to address participation inequalities.

Materials and Methods

Measures

AP Participation

We used data over three academic years (2013-14, 2015-16, 2017-18) from the US Department of Education's Civil Rights Data Collection (CRDC), a formerly biennial survey that covers all public schools in the US. Each school reported the number of students who were enrolled in at least one AP course (*course enrollment*), took at least one AP exam for the AP courses they were enrolled in (*exam taking*), and received a score of 3 or higher out of 5 for at least one AP exam they took (*exam passing*; not collected in 2017-18) for each racial group. Schools were included if there were a sufficient number of Black and White students to calculate Black-White AP participation gaps, defined as ten or more students in each group enrolled in grades 9-12 (for calculating AP course enrollment gaps), enrolled in at least one AP course (for exam taking gaps), or took at least one AP exam (for exam passing gaps). In 2017-2018, this screening left 8,528 schools across 1,667 counties with 1.7 million Black and 5.2 million White students for the enrollment gaps analysis (see *Appendix A* for sample sizes for earlier years).

Total Enrollment

Each school reported to the CRDC the total number of students enrolled in the school for each racial group across all grades. Following prior work (Xu et al., 2021), this data was combined with the Common Core Data (CCD), an annual dataset from the US Department of

Education that provides information on public schools. We then used the combined data to estimate the number of White and Black students enrolled in grades 9-12 only, which are eligible for AP courses (see *Appendix A* for details). These estimates were used as the denominator to calculate AP course enrollment rates for each racial group.

Regional Racial Bias

Project Implicit data was used to derive county-level estimates of implicit and explicit racial bias. Implicit bias was operationalized as the Implicit Associations Test (IAT) D-score, and explicit bias as the difference in self-reported warmth toward White versus Black Americans. Following prior work (Riddle & Sinclair, 2019), we included data from participants who completed the survey on or before the year the CRDC data was collected, reported age and geolocation, and identified as White (given this group's dominant role in shaping educational policy and outcomes; Diamond & Lewis, 2022). To avoid using overlapping data for the predictor and the interpersonal mediator (teachers' racial bias), we excluded participants who identified as teachers. In 2017-18, this yielded estimates for 3,124 counties based on 2.2 million participants.

Project Implicit is a nonrepresentative sample, as anyone interested can visit the website and take the survey. As such, merely aggregating individual observations may not accurately represent the county's true population. To address this, we used multilevel regression and post-stratification (MrP), as recommended in prior studies (Leitner et al., 2016; Riddle & Sinclair, 2019), to obtain more accurate county-level estimates of bias. Given that Project Implicit sample tends to be younger (Leitner et al., 2016) and that older people exhibit greater implicit bias than younger people (Gonsalkorale et al., 2009), we post-stratified on age to match the age distribution of Project Implicit sample to the actual age distribution of the county population.

Covariates

Covariates were obtained from the American Community Survey (ACS). Following prior work (Riddle & Sinclair, 2019), they included population size and proportions (total population, proportion of population White, proportion of population Black), socioeconomic indicators (unemployment rate, median income, poverty rate, college graduation rate, and their Black-White differences), urban-rural indicator (housing density), mobility, and segregation, all at county-level. We used estimates across 5 years, ending in the year of CRDC data collection (e.g., estimates across 2014-18 when analyzing the 2017-18 CRDC data).

Mediators

Concentration of AP Courses in Predominantly White Schools (Structural). To capture how AP course availability varies by schools' racial composition, we used the number of AP courses offered at each school from the CRDC data, as well as race-specific grades 9-12 enrollment. For each county, we calculated the correlation between the number of AP courses and the relative representation of White students, defined as the difference between the proportions of White and Black students in grades 9-12. To obtain a correlation that is not a perfect fit, this index was calculated only for counties with three or more schools in the analytic sample.

Prior Achievement Gap (Developmental). We used the Educational Opportunity Project v4.1 data from the Stanford Education Data Archive to assess students' academic achievement prior to high school. The data compiles standardized test scores in mathematics and reading, administered in grades 3-8 through 2008-2018, and provides estimates comparable across counties. The comprehensiveness of the data and the comparability of estimates make it a

suitable proxy for students' achievement prior to high school. We used county-level estimates of Black-White achievement gaps averaged across subjects, grades, and school years.

Teacher Racial Bias (Interpersonal). To estimate county-level implicit and explicit bias among teachers, we used Project Implicit data from participants who identified as White, aged 18 or older, reported their geolocation, and identified as teachers (either "Postsecondary Teachers," "Primary, Secondary, and Special Ed Teachers," or "Other Teachers and Instructors"). In 2017-18, this screening yielded approximately 175,000 participants across 2,795 counties. We applied the same MrP procedure used for estimating overall bias. To avoid deriving bias estimates from a small sample of teachers, we included only counties with at least 10 teachers. For post-stratification, we used state-level data on the age distribution of public school teachers from the National Teacher and Principal Survey, as county-level data specific to White teachers was unavailable.

Teacher Sexuality Bias (Interpersonal Robustness Checks). Implicit sexuality bias was operationalized as the IAT D-score testing associations between straight/good and gay/bad. Explicit sexuality bias was calculated as the average of the differences in self-reported warmth toward straight versus gay men, and toward straight versus gay women. We used data from White participants aged 18 or older who reported geolocation and identified as teachers, leaving approximately 59,000 participants across 2,444 counties in 2017-18. Following the same MrP procedure, we estimated county-level teacher sexuality bias for counties with at least 10 teachers who completed the sexuality bias survey.

To compare the explanatory value of the three mediators, the mediator analysis included only counties for which data on all three mediators were available. In 2017-18, this screening left 6,885 schools across 619 counties, representing 80.7% of schools and 37.1% of counties

included in the main analysis assessing the relationship between overall bias and Black-White AP enrollment gaps.

Chapter 2: Do Teachers' Racial Biases Predict Biased AP Placement Decisions?

Extant social psychological research on educational inequality has largely focused on student psychology, such as their concerns about bias (Spencer et al., 2016), sense of belonging (Walton & Cohen, 2011), and mindset about their academic ability (Macnamara & Burgoyne, 2023). However, students' beliefs, feelings, and outcomes are also shaped by the larger school environment they are part of. Emerging research has begun to explore the role of *teachers*, whose attitudes and beliefs may influence how they evaluate and interact with students, ultimately shaping their academic trajectories and performance (Turetsky et al., 2021).

Teachers play an especially important role in determining student outcomes when it comes to selecting participants for highly selective opportunities that allow students to realize and develop their full potential, such as gifted programs, honors, and Advanced Placement courses. These "opportunities for excellence" often involve identification processes that include teacher referrals (Plucker & Peters, 2020). Even in the absence of formal processes, teachers can still exert indirect influence, such as by encouraging students to pursue these opportunities (Witenko et al., 2017) or responding to parents' requests to reserve these opportunities for their children (A. E. Lewis & Diamond, 2015).

Similar to the rest of the American population, however, teachers often exhibit racial biases (Starck et al., 2020), which could lead to disparate assessment, interaction, and treatment of students of different racial backgrounds. Previous research has documented that teachers generally hold lower expectations for stigmatized minority students compared to majority students and make fewer positive referrals for Black and Latinx students than for White students (Tenenbaum & Ruck, 2007). One study showed that after the introduction of a universal screening program for identifying gifted students (in lieu of screening only students referred by

their parents or teachers), the proportion of minority students placed in gifted programs increased substantially, suggesting that teachers may have had overlooked qualified minority students in their referrals (Card & Giuliano, 2016). Additional studies have shown that racial differences in expectation, referrals, and enrollment in advanced programs are more pronounced among White teachers than Black teachers. For example, Black students were evaluated as almost ten percentage points less likely to earn a college degree by their White teachers than Black teachers (Gershenson & Papageorge, 2018), less likely to be referred to gifted programs when taught by non-Black (mostly White) teachers (Grissom & Redding, 2016), and more likely to enroll in advanced tracks when there was at least one Black instructor teaching at the advanced level (Hart, 2020). Combined with research showing that White people exhibit robust implicit and explicit anti-Black bias whereas Black people do not (Morehouse & Banaji, 2024), these studies provide preliminary evidence that teachers' racial biases contribute to disparate outcomes for Black and White students—but only indirectly, as they do not directly measure the extent of biases teachers hold.

A small but growing body of work have begun to fill in this gap by directly measuring teachers' racial biases and examining their correlates to student outcomes. van den Bergh and colleagues (2010) found that Dutch teachers' implicit (but not explicit) attitudes toward Moroccan/Turkish versus Dutch students were associated with greater ethnic gaps in mathematics and reading grades. Similarly, Peterson and colleagues (2016) measured teachers' implicit associations of different ethnic groups (European, Māori, Asian) and academic success, and found that teachers' implicit preference of one ethnicity over the other predicted the favored students' performance in mathematics. Most recently, Carlana and colleagues (2022) surveyed a large sample of teachers in Italy (1,384 teachers recruited from over a hundred schools) of their

implicit Italian-positive/immigrant-negative bias and examined its correlates with their track recommendations for more than 23,000 students. Teachers' implicit bias did not moderate track recommendations for native Italian students, but it predicted more recommendations to vocational tracks and fewer recommendations to top-tier tracks for immigrant students. The analyses suggested that conditional on students' measured ability, if all teachers held no implicit bias, the native Italian-immigrant gap for top-tier track recommendations would be closed, and the gap for vocational track recommendations would be reduced by more than 50 percent.

While these field studies are high in external validity and have controlled for observable student characteristics (e.g., standardized test scores) when available, a more controlled test would involve examining whether more biased teachers evaluate *identical* students differently, based solely on whether the student is ostensibly a member of majority or minority group. However, results from experimental work are mixed. For example, one study found evidence consistent with field studies, showing that when asked to choose between an ethnic minority or majority student exhibiting more academically desirable qualities (e.g., readiness to be inspired by the subject), teachers who implicitly favor majority over minority students were less likely to select the minority student (Glock & Böhmer, 2018). In contrast, other studies found no association between teachers' implicit and explicit biases and differential evaluations of Black versus White students' work (Quinn, 2020), or even observed significant relationships in the *opposite* direction, such that teachers who held stronger implicit preferences for migrant over native students (associating migrant students with higher performance) gave *lower* grades to migrant students (Bonefeld & Dickhäuser, 2018). Additionally, these studies have not examined how teachers' biases correlate with their decisions about who to select for highly selective

opportunities—decisions that have greater implications for students' academic trajectories than one-off grading decisions.

Overview of Studies

Building on emerging research on teacher bias, the present research investigates whether White teachers with stronger racial biases make biased decisions in selecting students for highly selective opportunities, even when the students being considered are comparable except for their race. Biased decision-making could manifest as a greater likelihood of admitting White students or denying Black students access to such opportunities. We examine this question in the context of AP course placement, an ideal example of highly selective opportunities that often involve selection processes such as teacher referrals or recommendations (Finn & Scanlan, 2019).

Pilot Study

In this pilot study, we recruited participants who work in the education industry from Prolific and tested whether implicit and explicit bias predict biased decisions (either driven by prioritizing White students for AP course placements, deprioritizing Black students, or both).

Method

Participants

A total of 213 Americans who answered yes to Prolific's prescreening question, "You indicated that you worked in the education industry. Does your job involve teaching?" were recruited and completed the first part of the study. Among these, 151 completed the second part on time. Following preregistered exclusion rules, five participants who indicated that they answered randomly at some point throughout the study were dropped from the analyses. Additionally, two participants exhibited careless responding on the IAT and were excluded from the analyses, leaving 144 participants in the final sample (M_{age} = 37.9, SD_{age} = 10.7; 34.0% men,

62.5% women; 70.1% White, 9.7% Asian, 6.9% Latinx, 4.2% Black, 9.0% others). 77 participants indicated that they are currently teaching in K-12 schools ($M_{\text{years of teaching}}$ = 10.9, $SD_{\text{years of teaching}}$ = 7.3; 81.8% at public schools, 18.2% at private schools).

Procedure

Student Evaluations (Part 1). Participants were told to imagine that they are a member of a committee at a local high school determining which students should be offered a spot in the AP English class. They were also told that in this school, there are a limited number of spots in AP classes, such that not everyone who wish could enroll.

Participants then reviewed applications from six students, one at a time. Each student's application consisted of a recommendation form from a previous teacher, which included ratings across four metrics as well as one overall rating, and a short statement from the student on why they would like to take the AP English class (see Figure 2.1 for an example).

Figure 2.1. Example application for a moderately-qualified, Black student.

Teacher Recommendation Form
Franklin Lewis High School

Name: Terrell Jefferson ID: 09272
Date of Birth: 2007-10-14 Gender: Male Race/Ethnicity: Black

Please keep this form confidential. You are asked to fill out this form for the student named above as his teacher for English II, Grade 10. A student will not be considered for enrollment into the AP English class without this form.

	Poor (1)	Below Average (2)	Average (3)	Above Average (4)	Excellent (5)	Additional Comments
Academic Abilities: • Reading, writing, and analytical skills • Verbal expression • Originality/creativity • Motivation					√	
Work Habits/Participation: • Initiative, effort • Use of class time • Turns in quality work • Attendance • Positive participation in class activities/respect for class environment					√	Work is thorough
Out-of-Class Habits: • Time and stress management • Ability to prioritize • Homework completion • Preparation for class (completed reading, has materials, etc.)				√		Struggles with time management but eventually gets it done
Personal Qualities: • Maturity level • Reaction to criticism/setbacks • Respect for teacher and peers					√	

Overall, this student's skills and abilities make him/her: (choose one)
___ Highly prepared for success in AP English
_√_ Reasonably prepared for success in AP English
___ Somewhat prepared for success in AP English
___ Not yet prepared for success in AP English

Statement from the Student

I would like to take AP English class because it will be a worthwhile learning experience. I will get to read great pieces from well-known authors, learn how to critically analyze these texts, and write clear, well-informed essays. These skills would help me not just in college but also throughout my life. I heard this class will be very demanding, but I will try my best.

The applications varied in two dimensions: student race and qualification. *Race* was manipulated in two ways. First, race information was provided with other demographic information at the top of the recommendation form. Second, names that were validated from prior research to be associated exclusively with being Black (Terrell Jefferson, Jermaine Washington), White (Cody Nielsen, Scott McGrath), Asian (Chang Huang), or Hispanic (Juan Gonzalez) were used (Milkman et al., 2012; Xu, 2022). *Qualification* was manipulated by the quality of the application to test the possibility that implicit bias matters only when evaluating moderately qualified (vs. clearly not qualified) students, in line with the aversive racism theory (Dovidio & Gaertner, 2000). Recommendation forms for moderately qualified students described the student as Excellent (5) in three out of four metrics, compared to only one metric for low-qualified students; similarly, statements from moderately qualified students were longer and reflected a better understanding of what the AP course has to offer than those from low-qualified students. All applications were piloted to ensure that perceived competence was different between levels (e.g., moderate applications perceived as describing a more qualified student than low applications) but similar within levels (e.g., all moderate applications perceived as describing an equally qualified student).

Among the six applications, two key applications described a moderately qualified applicant, one paired with a Black name and the other with a White name. Another two key applications described a low-qualified applicant, one paired with a Black name and the other with a White name. The remaining two applications were filler forms, one describing a highly qualified student (rated as Excellent in all four metrics) and the other a moderately qualified student, one paired with an Asian name and the other with a Hispanic name. The applications were presented in a random order, except that the filler application describing a highly qualified

student was always presented first to calibrate participants' expectations about how qualified a student should be to get into AP courses. After reviewing each application, participants answered four different questions, two concerning placement decisions and the other two concerning their expectations of how well the student would perform in the AP class and exam. Only responses to the four key applications were used in the analyses.

Upon completing evaluating all six students, participants answered demographic questions. Before exiting the survey, they were informed that they would be invited to the second part of the study the next day, and that they need to complete it within 48 hours.

Racial Bias (Part 2). A day after completing the first survey, participants were invited to the second survey assessing their racial bias. They completed an Implicit Associations Test (for measuring implicit bias) and a series of feeling thermometer questions (for explicit bias). The order in which they completed the IAT and feeling thermometer was randomized.

Measures

Student Evaluations (Part 1). For each of the six applications, participants provided their placement decisions on two questions: "Based on this student's qualifications, would you recommend this student for enrollment in the AP English class?" (*Yes* or *No*), and "Remember there is a considerable demand for the AP English class, such that there is not space for everyone who applies to get in. In which priority tier would you put this student?" (3 = *Should be ensured placement,* 2 = *Should be a top candidate to be placed, given sufficient space,* 1 = *Should only be placed if there are unfilled available spots,* 0 = *Should not be placed*).

While we preregistered the placement decisions as our primary outcome variables, we also measured participants' expectations of the student's performance with two items: "How successful do you think this student will be in the AP English class?" and "How well do you

think the student will do on the AP English exam?" (on a scale of 1 = *Not at all successful / Very poorly* to 10 = *Very successful / Very well*).

Racial Bias (Part 2). Participants' implicit bias was operationalized as the Implicit Associations Test (IAT) D-score, and explicit bias as the difference in participant's self-report of how warmly they feel toward White versus Black Americans. Higher scores indicated greater pro-White/anti-Black attitudes.

Analytic Strategy

For each outcome variable, we ran a linear mixed-effect model to examine whether implicit bias was associated with prioritizing White students, deprioritizing Black students, or both. The models included fixed effects of the three-way interaction of student qualification, student race, and participant bias (either implicit or explicit), and all lower-level effects. Given the nested structure of the data (each participant evaluating multiple students), the models also included random intercepts and random slopes of student qualification and race by participants.

For intuitive interpretations, sum-to-zero contrasts were used for all categorical variables (student qualification and race), such that the main effect of bias represents whether more biased participants *generally* rate students in a more stringent manner, across both levels of qualification and race. We then followed up with simple slope analyses to unpack the interaction of student race and participant bias—that is, to examine whether this interaction, if any, was driven by biased individuals prioritizing White students (i.e., positive slope concerning White students), deprioritizing Black students (i.e., negative slope concerning Black students), or both. The confirmatory analyses estimated these slopes across both levels of qualification, although we examined moderation by qualification on an exploratory basis. Across studies, we found no consistent moderation for both implicit and explicit bias.

Results

The results for our preregistered primary outcome variables (placement into one of the four priority tiers, binary admit/deny decision) are reported below. Results for expected performance were largely similar to the priority tier decision, albeit weaker (see *Appendix B*).

Priority Tier Decision

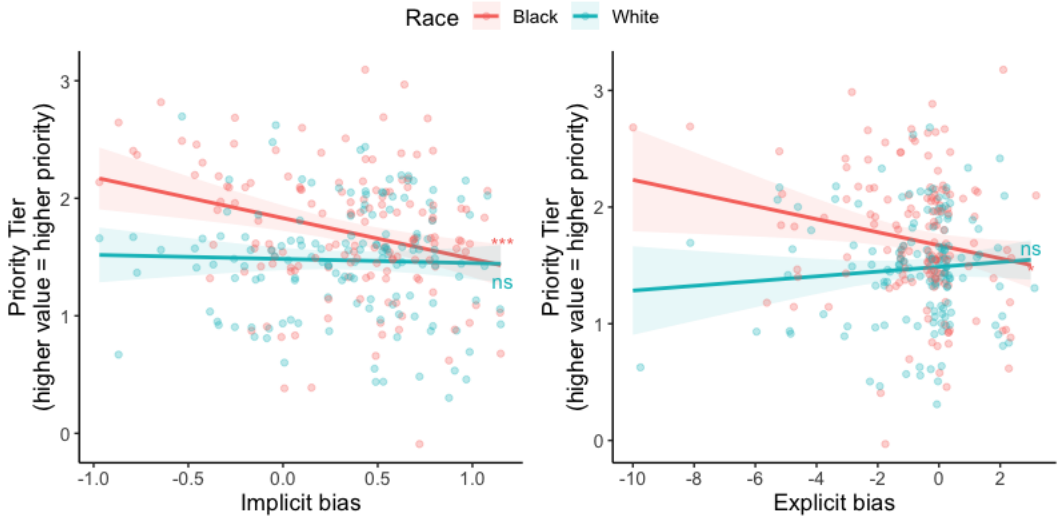
Implicit Bias. The main effect of implicit bias was significant (b = -0.192, SE = 0.078, p = 0.015, 95% CI [-0.346, -0.037]), indicating that more implicitly biased participants placed students more stringently. The main effect of race was also significant (b = -0.348, SE = 0.052, p < 0.001, 95% CI [-0.451, -0.244]), with White students placed into lower priority tiers than Black students. While this stands in contrast to the persistent underrepresentation of Black students in the actual AP classrooms (Patrick et al., 2020), this "pro-Black bias" was also demonstrated in similar social judgments tasks (Axt, 2017; Axt et al., 2016), potentially reflecting participants' social desirability concerns or different standards when evaluating Black versus White students (Biernat, 2009).

Importantly, these main effects were qualified by the hypothesized interaction between implicit bias and race (b = 0.313, SE = 0.093, p = 0.001, 95% CI [0.129, 0.497]). Simple slope analyses unpacking this interaction revealed that greater implicit bias predicted placement of Black students into lower priority tiers (b = -0.348, SE = 0.096, p < 0.001, 95% CI [-0.538, -0.158]), but not of White students (b = -0.035, SE = 0.085, p = 0.681, 95% CI [-0.204, 0.133]; Figure 2.2, left panel). Put differently, although the results did not fully reflect real-world disparities (underrepresentation of Black students in AP classrooms), the general patterns were consistent with meta-analytic findings that pro-White/anti-Black implicit bias is more strongly

associated with negative behavior toward Black targets than with positive behavior toward White targets (Oswald et al., 2013).

Explicit Bias. The pattern for explicit bias was generally the same. The main effect of explicit bias was not significant (b = -0.018, SE = 0.019, p = 0.349, 95% CI [-0.056, 0.020]) but the main effect of race was (b = -0.185, SE = 0.045, p < 0.001, 95% CI [-0.274, -0.095]), again indicating that White students were generally placed into lower tiers than black students. This main effect was again qualified by the hypothesized interaction between explicit bias and race (b = 0.076, SE = 0.022, p = 0.001, 95% CI [0.032, 0.120]). Specifically, greater explicit bias predicted placement of Black students into lower tiers (b = -0.056, SE = 0.024, p = 0.019, 95% CI [-0.103, -0.009]), but not of White students (b = 0.020, SE = 0.020, p = 0.319, 95% CI [-0.020, 0.061]; Figure 2.2, right panel).

Figure 2.2. Associations between priority tier placement and Prolific educators' implicit (left) and explicit (right) bias for Black and White students separately.



Note. Bias scores are raw values (i.e., zero indicates equal preference for Black and White individuals) and are displayed from the minimum to the maximum value in our data.

Binary Decision

As a more conservative test of the hypothesis, we also examined whether similar patterns are observed when using a less granular placement decision: either admit the student or not. Given the binary nature of this measure, logistic regression was used. When the fully sloped model did not converge, we simplified the model by including only random intercepts by participants following the preregistered analysis plan.

Implicit Bias. Similar to the priority tier decision, the main effect of race was marginally significant ($p = 0.060$), with White students slightly less likely to be admitted to the AP course than Black students. However, neither the main effect of implicit bias nor the interaction between implicit bias and race was significant (ps > 0.274). Simple slope analyses further indicated that implicit bias was not associated with the likelihood of placement for either Black or White students (ps > 0.174).

Explicit Bias. The analysis revealed no significant effects of race, explicit bias, or their interaction (ps > 0.216). Similar to implicit bias, explicit bias did not predict the likelihood of placement for either Black or White students (ps > 0.269).

Discussion

In the pilot study with 144 individuals who reported working in the education industry, we found preliminary evidence supporting our hypothesis that educators' racial bias may contribute to disparate AP enrollment outcomes. Greater implicit and explicit bias was associated with placing Black students into lower priority tiers, but not White students. However, this finding did not hold for a more conservative placement measure (admit or not).

Study 1

The primary goal of Study 1 was to conduct a preregistered replication with a population directly relevant to students' AP enrollment outcomes: White public high school teachers. We focused on Whites because White teachers constitute nearly 80% of the public school teaching workforce (NCES, 2020), yet they exhibit robust pro-White/anti-Black bias (Morehouse & Banaji, 2024; Starck et al., 2020), which may contribute to disparate expectations and treatment of Black students (Gershenson & Papageorge, 2018; Grissom & Redding, 2016). Additionally, we focused on public schools given the well-documented racial disparities in AP enrollment within these settings (Patrick et al., 2020).

Method

Participants

Participants were recruited from Qualtrics's research panels. Among 2,148 participants invited, 1,080 participants were not eligible to participate, either because they were not public high school teachers or did not identify as White. Among the remaining 1,068 participants, 763 participants did not pass our attention check for Part 1 (described in detail below) and were not allowed to proceed to Part 2. Ten participants indicated that they answered randomly at some point throughout the study, and two additional participants exhibited careless responding patterns on the IAT, leaving 293 participants included in the final sample (M_{age} = 43.1, SD_{age} = 10.5; $M_{\text{years of teaching}}$ = 12.4, $SD_{\text{years of teaching}}$ = 8.9; 51.5% men, 48.1% women).

Procedure

Procedures were largely similar to the pilot study, with three exceptions. First, Part 1 and 2 were now administered with no lag in between to minimize attrition. Second, given the limited availability of participants meeting our eligibility criteria, we allowed participants to use either a desktop computer or a mobile device (unlike in the pilot study, in which only desktop users were

allowed to participate). Third, to ensure that participants reviewed the materials carefully, we allowed only participants who passed the attention check for Part 1 to proceed to Part 2.

Measures

All student evaluations and racial bias measures were identical to the pilot study.

Attention Check (Part 1). Participants completed an attention check right after they finished reviewing applications and made placement decisions for all six students. Specifically, participants were asked which information about students was available in the materials they just reviewed, with correct answers (Name, Date of Birth, Gender, Race/Ethnicity, Teachers' ratings of students on four qualities, Teachers' comments, Students' statement on why they'd like to take the AP course) and fillers (GPA, Grades in standardized exams, Courses taken, Extracurriculars) presented as options. Those who selected all critical options (Name, Race/ethnicity, Teachers' ratings, Teachers' comments, Students' statement) and did not select any of the fillers were considered as a pass, following a preregistered decision after examining response patterns from the first 30 participants.

AP Policy. After completing the attention check but before starting Part 2, participants answered open-ended questions about AP enrollment policy at their schools. Participants first answered if the school they are currently teaching at offers AP courses. Those who responded yes were subsequently asked to describe how students enroll in AP courses (e.g., whether they need to apply to be considered for admission, and if yes, what is the application process like).

Results

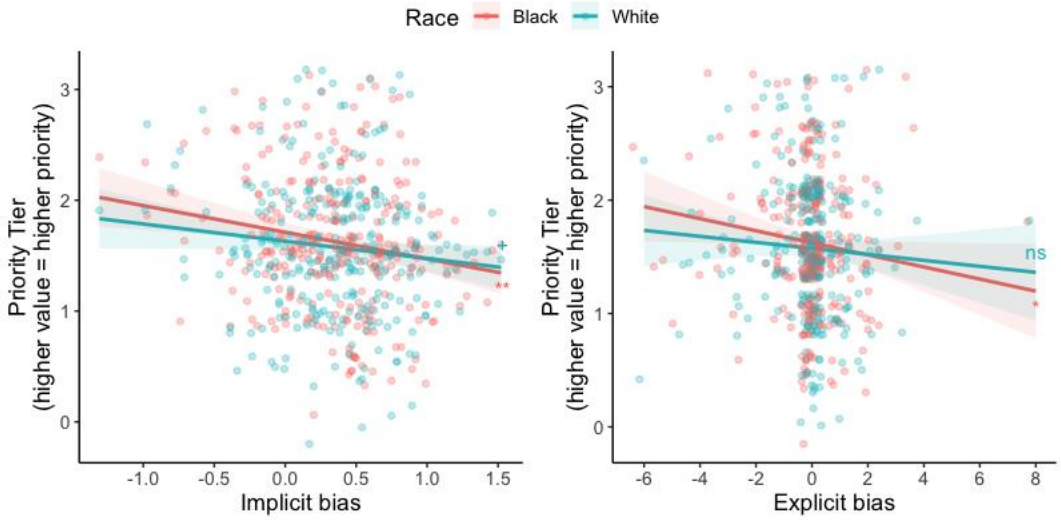
The same analytical model as in the pilot study was used. Results for the preregistered primary outcome variables (priority tier decision, binary decision) are reported below.

Priority Tier Decision

Implicit Bias. The analysis revealed significant main effects of implicit bias (b = -0.198, SE = 0.071, p = 0.005, 95% CI [-0.337, -0.059]) and race (b = -0.081, SE = 0.041, p = 0.049, 95% CI [-0.161, -0.0005]). However, unlike in the pilot study, these main effects were not qualified by the hypothesized interaction (b = 0.085, SE = 0.073, p = 0.243, 95% CI [-0.058, 0.229]). In this sample, implicit bias predicted significantly lower tier placement for Black students (b = -0.241, SE = 0.078, p = 0.002, 95% CI [-0.395, -0.086]) and marginally lower placement for White students (b = -0.155, SE = 0.080, p = 0.054, 95% CI [-0.313, 0.003]; Figure 2.3, left panel). In other words, while the negative effect of implicit bias on placement decisions appeared stronger for Black students than for White students, this difference was not statistically significant (as reflected in the null interaction).

Explicit Bias. The main effect of explicit bias was marginally significant (b = -0.040, SE = 0.023, p = 0.087, 95% CI [-0.085, 0.006]). Neither the main effect of race (b = -0.049, SE = 0.032, p = 0.130, 95% CI [-0.112, 0.14]) nor the hypothesized interaction between explicit bias and race was significant (b = 0.027, SE = 0.024, p = 0.260, 95% CI [-0.020, 0.074]). Explicit bias predicted significantly lower tier placement for Black students (b = -0.053, SE = 0.026, p = 0.040, 95% CI [-0.104, -0.002]) and not for White students (b = -0.026, SE = 0.026, p = 0.316, 95% CI [-0.078, 0.025]), but the null interaction indicated that these slopes do not significantly differ from each other (Figure 2.3, right panel).

Figure 2.3. Associations between priority tier placement and high school teachers' implicit (left) and explicit (right) bias for Black and White students separately (Study 1).



Note. Bias scores are raw values (i.e., zero indicates equal preference for Black and White individuals) and are displayed from the minimum to the maximum value in our data.

Binary Decision

Implicit Bias. The analysis yielded only a significant main effect of implicit bias (p = 0.027). Neither the main effect of race nor the interaction between implicit bias and race was significant (ps > 0.693). Similar to the priority tier decision, implicit bias predicted significantly lower likelihood of admitting Black students (b = -1.090, SE = 0.553, p = 0.049, 95% CI [-2.174, -0.006]) and marginally lower likelihood of admitting White students (b = -1.025, SE = 0.551, p = 0.063, 95% CI [-2.104, 0.054]), the null interaction indicating no significant difference between these slopes.

Explicit Bias. The analysis revealed no significant effects of race, explicit bias, or their interaction (ps > 0.634). Simple slope analyses revealed that explicit bias was not associated with placement likelihood for both Black and White students (ps > 0.830).

Discussion

In a study with White public high school teachers, we found limited support for our confirmatory hypotheses. Teachers' racial bias was generally associated with less favorable placement decisions for both Black and White students, but there was no evidence for differential effects, as indicated by null interactions observed across both types of bias and placement decisions.

One possible explanation for the null results is that the inclusion criteria were overly stringent. Bias may reflect a general tendency toward strictness or conservatism in decision-making, and this tendency may affect Black students relatively more than White students under typical circumstances. However, the attention check may have excluded less attentive participants, leaving only a highly attentive subset of teachers who were particularly cautious to avoid irrelevant cues (i.e., race) influence their placement decisions. If this was the case, the disproportionate impact of bias on Black students may have been attenuated. Indeed, 763 out of 1,068 participants (71.4%) failed the attention check and were excluded, resulting in a small, non-representative sample of teachers who completed the study.

Study 2

Study 2 was a replication of Study 1 with the inclusion criteria relaxed, to include a broader range of teachers with varying levels of attentiveness.

Method

Participants

Similar to Study 1, participants were recruited from Qualtrics's research panels. Among 2,339 participants invited, 1,907 participants were not eligible to participate, either because they were not public high school teachers or did not identify as White. Among the remaining 412 participants, 99 participants did not pass our attention check (as described below) and were not

allowed to proceed to Part 2. Ten participants indicated that they answered randomly at some point throughout the study, and three additional participants exhibited careless responding patterns on the IAT, leaving 300 participants included in the final sample (M_{age} = 41.8, SD_{age} = 13.2; $M_{years\ of\ teaching}$ = 12.2, $SD_{years\ of\ teaching}$ = 9.5; 42.3% men, 57.3% women).

Procedure

All procedures were identical to Study 1.

Measures

All student evaluations and racial bias measures were identical to previous studies.

Attention Check (Part 1). Participants completed the same attention check as in Study 1 after they made placement decisions for all six students. The inclusion criteria were relaxed, such that participants who indicated that they recall seeing the key manipulation (either race or name) were now considered as a pass.

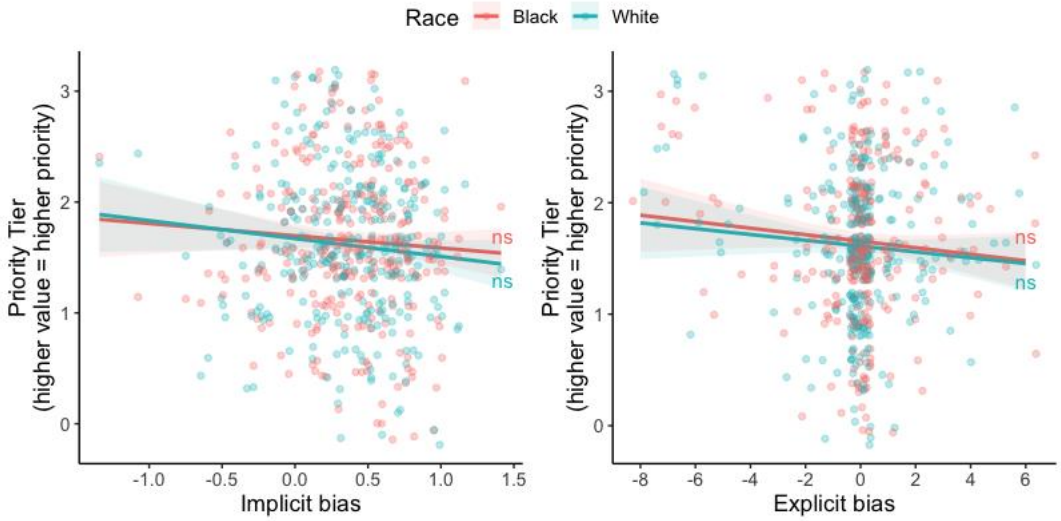
Results

The same analytic model as in previous studies was used. In this study, we preregistered the priority tier decision as our confirmatory outcome variable, given the stronger support for this measure in the pilot study (likely due to greater variance it provides). However, we also report the results for binary decision for consistency with prior studies.

Priority Tier Decision

In this sample, neither the main effects of race, bias, or their interaction were significant (ps > 0.123 for implicit bias; ps > 0.130 for explicit bias). Simple slope analyses revealed that neither implicit nor explicit bias was associated with tier placement for both Black and White students (ps > 0.101 for implicit bias; ps > 0.155 for explicit bias; Figure 2.4).

Figure 2.4. Associations between priority tier placement and high school teachers' implicit (left) and explicit (right) bias for Black and White students separately (Study 2).



Note. Bias scores are raw values (i.e., zero indicates equal preference for Black and White individuals) and are displayed from the minimum to the maximum value in our data.

Binary Decision

Similar to the priority tier decision, neither the main effects of race, bias, or their interaction were significant (*p*s > 0.412 for implicit bias; *p*s > 0.074 for explicit bias). Again, neither implicit nor explicit bias was associated with the likelihood of placing for both Black and White students (*p*s > 0.355 for implicit bias; *p*s > 0.285 for explicit bias).

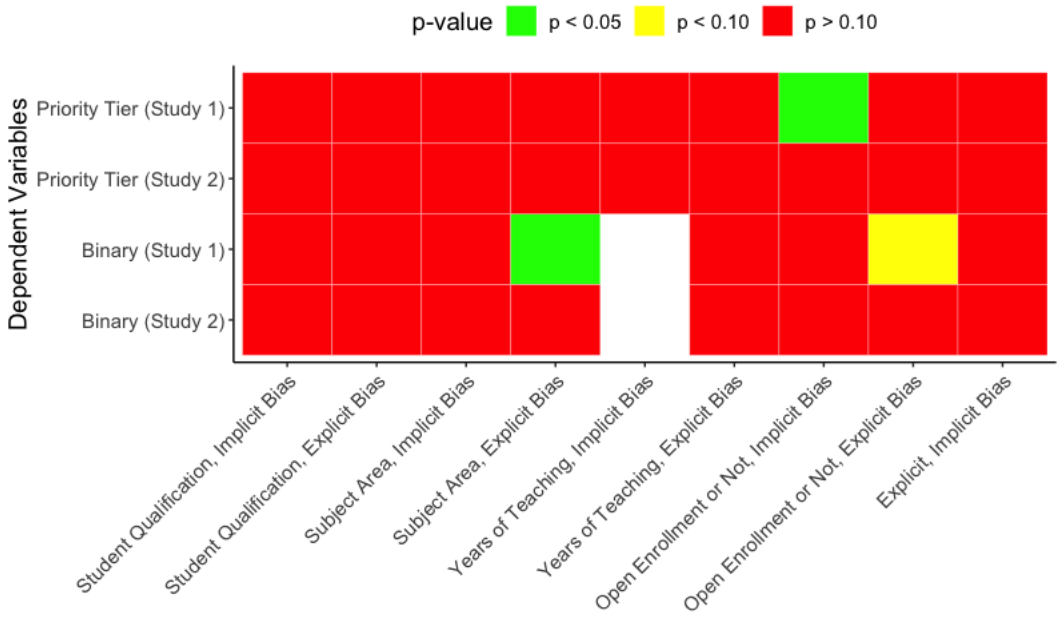
Exploratory Moderation

Given the pervasive null effects observed across Studies 1-2, we explored several student- and teacher-level attributes that could moderate the relationship between teacher bias and placement decisions. For student-level attribute, we examined student qualification, drawing on aversive racism literature that suggests discrimination is more pronounced in ambiguous situations (e.g., when the target is neither clearly qualified nor unqualified; Dovidio & Gaertner, 2000). For teacher-level attributes, we considered relevant experience, operationalized as their subject area (English or not), years of teaching experience, and whether they taught at schools

with open (vs. closed) AP enrollment policy. We also considered the interaction of implicit and explicit bias and examined whether the effects of implicit bias, if any, would be stronger among participants with low levels of explicit bias, as predicted by aversive racism theory.

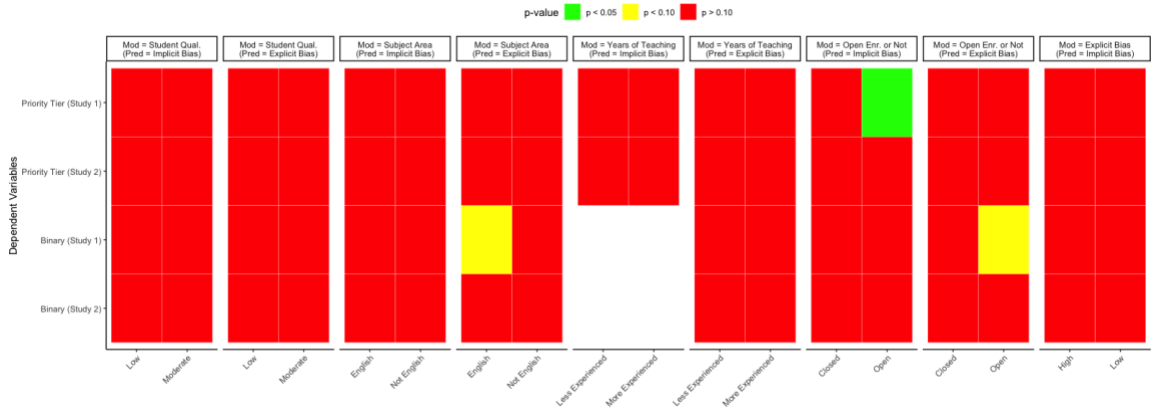
Only two of these tests identified significant moderators (i.e., a three-way interaction between race, bias, and the moderator with $p < 0.05$), with no consistent patterns across studies or dependent variables, indicating that these are likely due to chance (Figure 2.5a). Given the possibility that our studies were underpowered to detect a three-way interaction, we further examined the two-way interaction between race and bias at each level of the moderator. These analyses again revealed that no specific moderator value consistently resulted in the hypothesized relationship between teacher bias and placement decisions (i.e., a significant two-way interaction at $p < 0.05$; Figure 2.5b).

Figure 2.5a. Heatmap of results from the exploratory analyses examining the three-way interaction between race, bias (implicit or explicit), and moderator.



Note. Blank cells indicate models that did not converge.

Figure 2.5b. Heatmap of the results from exploratory analyses examining the two-way interaction between race and bias (implicit or explicit) at each level of the moderator.



Note. Blank cells indicate models that did not converge.

Discussion

In a replication of Study 1 where we relaxed the eligibility criteria to address selection bias, we again found little support for the confirmatory hypotheses. In this sample, teachers' implicit and explicit bias did not predict placement decisions for both groups. Furthermore, across Studies 1-2, we found no consistent moderation by students' qualifications or teachers' relevant experience with making similar types of decisions.

General Discussion

Teachers' racial bias has been identified as one driver of racial inequality in schools (Warikoo et al., 2016). Consistent with this perspective, White teachers' implicit and explicit pro-White/anti-Black bias was found to be associated with greater Black-White disparities in AP course enrollment at the county level (Chapter 1). A pilot study with educators suggested that similar dynamics may occur at the individual level, with more biased educators making biased decisions (placing Black students into lower priority tiers, but not White students) even when students being considered were equally qualified. However, results from the two experiments with White public high school teachers did not replicate these findings. In Study 1, teachers' bias was associated with less favorable placement decisions for both Black and White students to a comparable extent; in Study 2, teachers' bias was not associated with placement decisions for either group.

There are several different possibilities that could account for the inconsistent results across studies. One possibility is the sample differences—namely, whether we recruited educators broadly or high school teachers more specifically. The latter would be more likely to have direct experience making AP placement decisions, which may have better trained them to focus on relevant cues (e.g., student qualifications) rather than irrelevant ones (e.g., student race). In the field data analysis (Chapter 1), county-level estimates of teacher bias were derived from a broad range of teachers, including primary, special education, and postsecondary teachers; similarly, the pilot study recruited a broad sample, including not only teachers but also administrators and staff members. In contrast, the two main studies specifically recruited public high school teachers, a sample more directly relevant to AP placement. Several factors caution against attributing the inconsistent results across studies solely to sample differences. First, even

if these broader educator groups lack direct experience with AP placement, they still make similar selection decisions, such as determining who qualifies for gifted programs (primary teachers) or advanced courses (postsecondary teachers). Second, in the main experiments, we found no consistent evidence that teachers with less experience (e.g., fewer years of teaching, or working at schools without an application process for AP enrollment) made decisions differently from their more experienced counterparts. Nonetheless, it remains possible that more relevant experience in making AP placement decisions—especially when interacted with certain contextual cues—may have reduced the influence of biases on placement decisions among high school teachers.

One such contextual factor is the salience of teachers' professional identity, which may have been amplified in the main studies by the placement of the occupation questions. In the pilot study, these questions were asked at the end of the survey, whereas in the main studies, they appeared at the beginning. Although this change was necessary to ensure that we recruited our target sample only (public high school teachers), it may have inadvertently made participants' professional identity more salient. This heightened awareness could have motivated participants to approach placement decisions more impartially. As a result, even teachers with high levels of implicit and explicit bias may have made unbiased decisions toward Black and White students, potentially explaining the null results observed in the main studies.

Both possibilities postulate that high school teachers—whether due to their relevant experience with making AP placement decisions, or their commitment to fair evaluations as teachers—may be better at *regulating* their racial biases, thereby preventing such biases from influencing student outcomes. Future research should directly test this assumption by examining contextual moderators that affect teachers' ability to regulate bias. Such moderators might

include time constraints, which could limit opportunities for deliberation, or a sense of accountability over student outcomes, which may motivate greater deliberation.

One contextual factor we directly examined is *cognitive load*, which could make it harder for teachers to regulate bias. Research on implicit bias suggests that high cognitive demands reduce individuals' capacity for controlled processing, thereby increasing reliance on automatic processing and biases (Feldon, 2007; Friese et al., 2008). For example, lab studies have shown that experimentally inducing cognitive load—by requiring participants to memorize nonsense words or long-digit numbers—leads to greater reliance on stereotypes (Goldinger et al., 2003; Wigboldus et al., 2004). More recently, Singh and colleagues (2020) found that while training participants improved performance on a shooter task (i.e., reduced tendency to shoot Black targets compared to White targets), this improvement disappeared under high cognitive load.

Applying these findings to AP placement decisions, teachers under cognitively demanding conditions might similarly rely more on their biases (particularly implicit bias) when evaluating students. To test this possibility, we conducted a pilot experiment with 98 White public high school teachers, randomly assigning them to either a high- or low-load condition. Teachers were presented with either an 8-letter string (high-load) or a 2-letter string (low-load) and were instructed to retain the string while evaluating students. After completing the placement task, they completed a string recall question, compliance checks, and implicit and explicit bias measures. We hypothesized that implicit bias would predict biased decision-making only in the high load condition, given that cognitive demands would increase reliance on automatic processing and biases, and did not hypothesize differences between conditions for explicit bias.

Results from this pilot study did not support cognitive load as a moderator of implicit bias. Implicit bias did not predict placement decisions for either Black or White students in either

condition, yielding null interactions in both cases (ps > 0.405). A similar pattern emerged for explicit bias (ps > 0.179; see *Appendix B* for full statistics). More critically, participants' responses raised concerns about the effectiveness of the cognitive load manipulation and data quality. Participants in both conditions reported paying similar levels of attention to the letter string while evaluating students, suggesting that the manipulation may not have induced cognitive load effectively. Additionally, nearly half of the participants reported at least one instance of noncompliance (e.g., using shortcuts such as writing down the string or not attempting to remember it at all). Given these issues, we did not proceed with a full-scale study. However, future research should explore alternative methods to assess whether cognitive load moderates the influence of implicit bias in placement decisions. For instance, conducting an in-lab study—where compliance can be closely monitored—may yield more reliable results.

Research focusing on teachers is essential, given their central role in shaping students' academic experiences. A growing body of work has demonstrated the effectiveness of teacher-focused interventions, such as targeting teachers' mindsets (Canning et al., 2019) and perceptions of students (Gehlbach et al., 2016), in reducing racial achievement gaps. If teachers' biases contribute to racial opportunity gaps, interventions aimed at teachers could also help ensure that all students have equal opportunities to demonstrate their potential. Although some evidence suggests that teachers' biases do contribute to disparities in participation in advanced learning opportunities (Chapter 1), the present research suggests that more work is necessary to understand when and how these biases translate into disparate outcomes. Addressing these questions would offer critical insights for developing more targeted and effective teacher-focused interventions.

Chapter 3: Implicit Bias and Hoarding of Valuable and Scarce Opportunities

Efforts to close racial achievement gaps have largely focused on addressing disparities at basic and proficient levels of attainment. However, relatively less attention has been given to closing gaps at advanced levels—a phenomenon referred to as excellence gaps (Plucker et al., 2010; Plucker & Peters, 2020). One reason for excellence gaps is the unequal participation in advanced learning opportunities. For example, Black students in some states are less likely to attend schools offering gifted and talented programs than students overall (Gentry et al., 2024), and schools with higher percentages of Black and Latinx students offer fewer Advanced Placement (AP) courses (Zarate & Pachon, 2006). Even within schools, Black students remain underrepresented in honors and AP courses (Clotfelter et al., 2021; Siegel-Hawley et al., 2021). One study has found that the more racially diverse the schools, the more likely White students were to be enrolled in college preparatory tracks, and the less likely Black students were (Lucas & Berends, 2007). These findings underscore the viability of race-based processes that systematically allocate advanced learning opportunities to White students over Black students.

One explanation for this pattern of racial disparities is opportunity hoarding, a concept from sociology and education scholarship. The opportunity hoarding framework theorizes that advantaged groups (typically White and/or middle- and upper-middle class) reinforce race and class inequalities by steering access to valuable and scarce opportunities toward their own group while excluding others (Tilly, 1998, 2007). This framework has been used to explain how advantaged families secure opportunities that enhance long-term academic and professional outcomes, such as admissions to highly sought-after K-12 schools (Denice et al., 2021; Sattin-Bajaj & Roda, 2020), placement in AP courses (Rodriguez & McGuire, 2019), prestigious internships (Hamilton et al., 2018), and STEM college degrees (Riegle-Crumb et al., 2019), often

at the expense of racial minorities and low-income students. Specific practices include both hoarding opportunities for the ingroup, such as by advocating for their children's advantages (e.g., overriding placement decisions and securing slots in advanced tracks; Lewis & Diamond, 2015) and excluding opportunities for the outgroup, such as by resisting efforts to desegregate schools and classrooms (Apple & Debs, 2021; Christ, 2018).

One mechanism theorized to underlie opportunity hoarding is the creation and endorsement of narratives that legitimize unequal access to resources (Diamond & Lewis, 2022). Advantaged group members often invoke race-based cultural beliefs to rationalize the underrepresentation of minority students in opportunities for excellence, attributing it to deficiencies in their academic ability or investment. For example, a thematic analysis of media coverage on detracking efforts in Germany revealed that opponents conflated intelligence with students' ethnicity, claiming that immigrant students would lower classroom standards and deprive "more intelligent," non-immigrant students of teachers' attention (Apple & Debs, 2021, p. 75). Similarly, White American parents attributed the underrepresentation of Black students in advanced tracks to Black students and families having "lower expectations than the typical average White family" (Lewis & Diamond, 2015, p. 145). However, this literature has been largely qualitative, leaving an empirical question of whether these race-based biases and stereotypes are, indeed, directly associated with the practice of opportunity hoarding.

Additionally, racial bias is not always explicitly expressed or endorsed (both generally and specifically in the context of opportunity hoarding), underscoring the need to consider the role of implicit bias. Generally, while overt expressions of prejudice have declined over time, implicit prejudice remains prevalent. Data from the Project Implicit survey indicate that only 29% of respondents reported explicit preferences for White over Black people, compared to 65%

who exhibited implicit preferences (Morehouse & Banaji, 2024). In the context of opportunity hoarding, qualitative research has shown that parents who engage in these practices often identify as egalitarians. For instance, some parents report choosing racially diverse public schools for their children precisely because they value the benefits of diverse learning environments (Roda & Wells, 2013). Yet when pressed to explain the basis of racial segregation along academic tracks within these schools, these parents often invoke aforementioned, race-based explanations rooted in cultural prejudices (A. E. Lewis & Diamond, 2015). Together, these patterns suggest that individuals with stronger biases measured implicitly—in addition to those with stronger explicit biases—may draw on subtle, readily available racial associations to justify their participation in opportunity hoarding.

Building on these insights, the present research examines whether White Americans' implicit biases are associated with opportunity hoarding. In particular, we examine whether implicit bias predicts biased decision-making in the context of AP course placement, a paradigmatic example of academic opportunities that White, middle-class parents and students have been shown to hoard. We define biased decision-making as instances where implicit bias differentially predicts outcomes for Black versus White students. Examples may include bias predicting worse outcomes for Black students, but not influencing or predicting better outcomes for White students.

Our research builds on the implicit bias literature by identifying novel moderators that amplify the link between implicit bias and biased decision-making. While implicit bias has been found to meaningfully correlate with intergroup discrimination, meta-analyses reveal considerable variability in effect sizes (Kurdi et al., 2019; Oswald et al., 2013). This heterogeneity highlights the need to identify factors that moderate the relationship between

implicit bias and behavioral outcomes (Gawronski, 2019), such as individuals' motivation to control prejudice (S. H. Park et al., 2008) or cognitive resource availability (Hofmann et al., 2008). Beyond these known factors, we propose that the scarcity and value of contested resources—qualities that make an opportunity worth hoarding (Reeves, 2018)—also moderate this relationship. Specifically, we explore whether implicit bias predicts biased decision-making when contested opportunities are scarce, valuable, or both.

Existing research provides support for each possibility. On one hand, scarcity alone may be sufficient. Scarcity promotes intergroup competition, fosters discrimination (Chae et al., 2022; Chattopadhyay & Bianchi, 2021; Sherif, 1966), and triggers biased cognitive processing that can justify such behaviors. For example, individuals primed with scarcity perceived Black faces as "Blacker" (Krosch & Amodio, 2014; Rodeheffer et al., 2012) and reported greater knowledge of stereotypes portraying Black people as low-SES and threatening (Berkebile-Weinberg et al., 2022). On the other hand, value alone may be sufficient. Ingroup favoritism can emerge even in noncompetitive contexts (Dunham et al., 2011; Tajfel & Turner, 1979), and highly valuable resources may intensify this tendency by motivating individuals to direct resources to their ingroup and enhance relative group status. Lastly, both scarcity and value may be necessary. Opportunities that are both scarce and valuable provide a uniquely powerful context for discrimination to arise, as they combine competition over limited resources with the potential for status gains. Such opportunities differ from valuable but abundant opportunities (which do not invoke competition) or scarce but low-value ones (which do not significantly enhance group status when attained). Together, all three possibilities reflect a motivational account in which scarcity, value, or both would heighten motivations to engage in discriminatory behaviors, and individuals who already harbor prejudices toward the outgroup may find it easier to do so.

However, most existing studies have not simultaneously examined the interplay between value, scarcity, bias, and discriminatory behaviors. The present research aims to address this gap by testing how value, scarcity, and implicit bias interact to predict biased decision-making.

Overview of Studies

The present research investigates whether White Americans' implicit bias predicts biased decision-making (Study 1), and whether this relationship is moderated by the value and scarcity of the contested opportunity (Studies 2-3). We examine this question in the context of AP course placement, a major example of advanced academic opportunities within the US education system that offers enhanced academic experiences in high school and improved prospects for college admissions (Finn & Scanlan, 2019).

We also explore whether explicit bias also predicts biased decision-making and whether the value and scarcity of the opportunity moderate this relationship. Across studies, explicit bias generally predicted biased decision-making, most times driven by explicit bias predicting worse outcomes for Black students but not for White students. This relationship emerged across contexts, suggesting that individuals tend to act in alignment with their explicitly endorsed beliefs regardless of the opportunity's value and scarcity. Accordingly, the main text focuses on the relationship between implicit bias and biased decision-making and how it varies by contexts, but see *Appendix C* for full results for explicit bias.

Study 1

Study 1 aimed to establish whether White Americans' implicit bias predict biased decision-making, either by prioritizing White students for AP course placement, deprioritizing Black students, or both.

Method

Participant

A total of 301 White Americans were recruited from Prolific and completed the first part of the study. Among these, 261 completed the second part on time. Following the preregistered exclusion rule, we excluded nine participants who indicated that they answered randomly (e.g., clicked an answer without reading the question or thinking about it) at some point throughout the study. We also excluded two participants who were identified as responding carelessly on the IAT (answered more than 10% of the critical trials faster than 300ms), leaving 250 participants in the final sample (M_{age} = 38.2, SD_{age} = 13.3; 50.0% men, 48.4% women).

Procedure

All procedures were identical to the pilot study from Chapter 2.

Measures

All student evaluations and racial bias measures were identical to the pilot study from Chapter 2.

Analytic Strategy

For each outcome variable, we ran a linear mixed-effect model to examine whether implicit bias was associated with prioritizing White students, deprioritizing Black students, or both. The models included fixed effects of the three-way interaction of student qualification, student race, and participant bias (either implicit or explicit), and all lower-level effects. Given the nested structure of the data (each participant evaluating multiple students[6]), the models also included random intercepts and random slopes of student qualification and race by participants.

[6] It is possible that social desirability concerns led participants to adjust their ratings over time (e.g., rating later applications more favorably than earlier applications) as they reviewed multiple applications. All applications—except the one featuring a highly qualified student, which was always presented first to calibrate expectations—were presented in a random order. Therefore, any social desirability effects should not systematically influence ratings of specific applications. Nevertheless, to address this concern, we re-ran the analyses using only the second application (i.e., application that appeared right after the highly qualified student), treating the data as a between-subjects

For intuitive interpretations, sum-to-zero contrasts were used for all categorical variables (student qualification and race), such that the main effect of bias represents whether more biased participants *generally* rate students in a more stringent manner, across both levels of qualification and race. We then followed up with simple slope analyses to unpack the interaction of student race and participant bias—that is, to examine whether this interaction, if any, was driven by biased individuals prioritizing White students (i.e., positive slope concerning White students), deprioritizing Black students (i.e., negative slope concerning Black students), or both. The confirmatory analyses estimated these slopes across both levels of qualification, although we examined moderation by qualification on an exploratory basis. Across studies, we found no consistent moderation for both implicit and explicit bias.

Results

The results for our preregistered primary outcome variables (placement into one of the four priority tiers, binary admit/deny decision) are reported below. See *Appendix C* for results modeling expected performance as the outcome, as well as results for explicit bias.

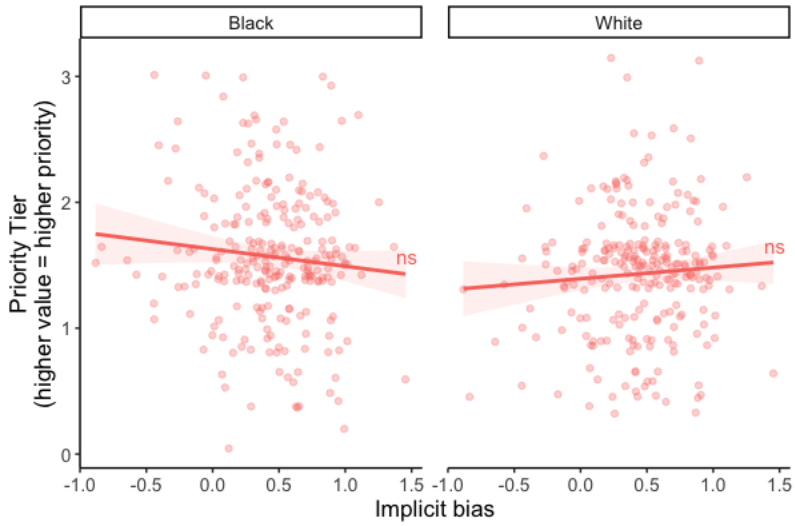
Priority Tier Decision

We found no significant main effect for implicit bias (b = -0.024, SE = 0.074, p = 0.752, 95% *CI* [-0.170, 0.123]), but a significant main effect for race (b = -0.236, SE = 0.048, $p < 0.001$, 95% *CI* [-0.331, -0.140]), such that participants placed White students into lower priority tiers than Black students. Importantly, the main effect of race was qualified by the hypothesized interaction between race and implicit bias (b = 0.225, SE = 0.083, p = 0.007, 95% *CI* [0.061, 0.389]). Simple slope analyses unpacking this interaction revealed that although neither slopes

experiment. Across studies (particularly Studies 1-2), results were weaker and not significant—likely due to the reduced statistical power—but the directional patterns remained consistent. See *Appendix C* for full statistics.

reached statistical significance, greater implicit bias was directionally associated with placing Black students into lower priority tiers (b = -0.136, SE = 0.090, p = 0.132, 95% CI [-0.313, 0.041]) and White students into higher tiers (b = 0.089, SE = 0.080, p = 0.267, 95% CI [-0.069, 0.246]; Figure 3.1).

Figure 3.1. Associations between priority tier placement and implicit bias by student race (Black vs. White).



Note. Bias scores are raw values (i.e., zero indicates equal preference for Black and White individuals) and are displayed from the minimum to the maximum value in our data.

Binary Decision

As a more conservative test of the hypothesis, we also examined whether similar patterns are observed when using a less granular placement decision: either admit the student or not. Given the binary nature of this measure, logistic regression was used. The fully sloped model did not converge, and we simplified the model by including only random intercepts by participants following the preregistered analysis plan.

We found largely similar patterns to the priority tier decision analyses. The main effect of implicit bias was not significant (b = 0.211, SE = 0.480, p = 0.660, 95% CI [-0.729, 1.151]) but

the main effect of student race was (b = -0.920, SE = 0.336, p = 0.006, 95% CI [-1.579, -0.262]), such that White students were generally less likely to be admitted into AP courses than Black students. Similar to priority tier decision, this main effect was qualified by a marginally significant interaction between race and implicit bias (b = 1.074, SE = 0.585, p = 0.066, 95% CI [-0.072, 2.221]). Simple slope analyses revealed that greater implicit bias was directionally associated with being more likely to admit White students (b = 0.748, SE = 0.551, p = 0.175, 95% CI [-0.333, 1.829]) and not associated with the likelihood of admitting Black students (b = -0.326, SE = 0.572, p = 0.569, 95% CI [-1.447, 0.795]).

Discussion

Study 1 found that, consistent with our hypothesis, White Americans' implicit bias predicted biased decision-making. Although we observed an unexpected overall preference for Black over White students—contrary to real-world patterns of underrepresentation of Black students in AP classrooms—this main effect was qualified by the hypothesized interaction with implicit bias. Specifically, greater implicit bias was directionally associated with prioritizing White students for placement and deprioritizing Black students.

Having established a link between implicit bias and biased placement decisions, we next conduct a more direct examination of the opportunity hoarding hypothesis—specifically, whether this relationship holds only for highly valuable and scarce opportunities deemed "worth hoarding."

Study 2

Study 2 aimed to identify the contexts under which implicit bias is linked to biased decision-making. Specifically, we assessed whether the said association is stronger when the AP course is described as a highly valuable and scarce opportunity than not.

Method

Participants

A total of 600 White Americans were recruited from Prolific and completed the first part of the study. Among these, 560 completed the second part on time. Similar to Study 1, we excluded seven participants who indicated careless responding on the IAT and five participants who indicated that they answered randomly at some point throughout the study. We also excluded five participants who identified themselves as Whites to Prolific's prescreening questions but did not identify as Whites to the demographic question in our survey, leaving 543 participants in the final sample, 274 in the *Valuable and Scarce* condition and 269 in the *Not Valuable and Not Scarce* condition (M_{age} = 42.6, SD_{age} = 13.5; 55.8% men, 42.2% women). Post-hoc power calculations indicated that the final sample size gave 81% power to detect a same-sized interaction between implicit bias and student race as in Study 1 within each condition.

Procedures

Procedures were largely similar to Study 1 except that now, before reviewing the application materials, participants were randomly assigned to read a short paragraph framing the AP program as either highly valuable and scarce or not. The paragraph described the benefits of taking AP courses for college admissions (either significant or minimal), the number of colleges awarding credits for qualifying AP scores (either increasing or decreasing), and the percentage of students at this high school typically admitted to AP courses (either a few or many).

After reading the stimuli, participants were presented with the same task description used in Study 1, except that it no longer mentioned that the slots are limited (given that we now directly manipulated the scarcity of AP courses). Participants then reviewed the same application materials from six students as in Study 1, evaluated each student, and completed the attention

and manipulation check questions, as described below. As in Study 1, they were invited to the second survey the following day, in which they completed implicit and explicit bias measures and were debriefed.

Measures

All student evaluations (Part 1) and bias measures (Part 2) were identical to Study 1. Given the stronger support for the priority tier decision in Study 1 compared to the more conservative admit/deny decision, as well as the fact that the priority tier decision likely better reflects real-world decision-making, we preregistered the priority tier decision as the confirmatory outcome variable. See *Appendix C* for the results for all other outcomes.

Attention Check (Part 1). Right after completing student evaluations, participants were asked which information about students was available in the materials they just reviewed, options including correct answers and fillers. Participants who did not select either *Name* or *Race/Ethnicity* were considered as failing the attention check. The rate of passing the attention check did not differ significantly between the conditions (93.8% for the *Valuable and Scarce* condition, 91.8% for the *Not Valuable and Not Scarce* condition; $\chi^2(1, 543) = 0.525$, $p = 0.469$). We did not preregister excluding participants who failed the attention check, but the results were stronger when excluding them (see *Appendix C*).

Manipulation Check (Part 1). After completing the attention check, participants also completed a question assessing their understanding of how scarce the opportunities are to take AP courses at this high school ("According to the information provided, how many students can enroll in AP classes at this high school?") by selecting one of the four options: *Very few, About half, Many, Anyone who applies get in*. While we did not preregister excluding participants based on their response to this question, we conducted exploratory analyses where we excluded

participants who selected the most incorrect answer ("Anyone who applies get in" for those assigned to the *Valuable and Scarce* condition, "Very few" for the *Not Valuable and Not Scarce* condition), and the results were stronger (see *Appendix C*).

Participants also answered a question assessing their perception of how valuable taking AP courses is for high school students on a scale of 1 = *Not valuable at all* to 5 = *Very valuable*.

Analytic Strategy

Following the preregistered analysis plan, we adapted the analytic approach used in Study 1. Specifically, we modeled priority tier ratings as a function of fixed effects of student qualification, race, experimental condition, participant bias (implicit or explicit), and their interactions. The model also included random slopes of qualification and race, as well as random intercepts, by participants. Again, for intuitive interpretation, sum-to-zero contrasts were used for all categorical variables (qualification, race, experimental condition). Under this scheme, the main effect of bias would indicate whether participants with higher bias placed students more stringently overall. Similarly, the interaction between student race and bias would indicate whether the hypothesized interaction (greater bias linked to biased placement decisions, driven by either prioritizing White students, deprioritizing Black students, or both) was observed overall, across experimental conditions. Finally, we examined the three-way interaction among race, bias, and condition to determine whether the hypothesized interaction between race and bias manifested differently when the AP program was described as a valuable and scarce opportunity versus not.

Results

Manipulation Check

The manipulation was successful at changing participants' perceptions of value of AP courses. Those assigned to the *Valuable and Scarce* condition rated AP courses as significantly more valuable ($M = 4.51$, $SD = 0.78$) than those assigned to the *Not Valuable and Not Scarce* condition ($M = 3.95$, $SD = 0.95$; $t(516.36) = -7.50$, $p < 0.001$). Most participants also correctly recalled how scarce are the opportunities to take AP courses at this school; 80.3% of participants in the *Valuable and Scarce* condition indicated that very few students get in, and 82.2% of those in the *Not Valuable and Not Scarce* condition indicated that all, many, or about half of the students get in.

Balance Check

Randomization was successful, such that there was no significant differences between the two conditions in either implicit (*Valuable and Scarce*: $M = 0.48$, $SD = 0.43$; *Not Valuable and Not Scarce*: $M = 0.51$, $SD = 0.37$; $t(531.16) = 1.00$, $p = 0.320$) or explicit bias (*Valuable and Scarce*: $M = 0.25$, $SD = 1.72$; *Not Valuable and Not Scarce:* $M = 0.21$, $SD = 2.02$; $t(523.85) = -0.23$, $p = 0.822$).

Main Analysis

The main effects of implicit bias, race, and their interaction followed similar patterns to Study 1. The main effect of implicit bias was not significant ($b = -0.026$, $SE = 0.056$, $p = 0.639$, 95% *CI* [-0.136, 0.084]). The main effect of student race was significant ($b = -0.159$, $SE = 0.035$, $p < 0.001$, 95% *CI* [-0.227, -0.090]), such that participants placed White students into lower priority tiers than Black students. This effect was qualified by a significant interaction between race and implicit bias ($b = 0.118$, $SE = 0.055$, $p = 0.031$, 95% *CI* [0.011, 0.225]). Specifically, greater implicit bias was directionally associated with placing Black students into lower priority

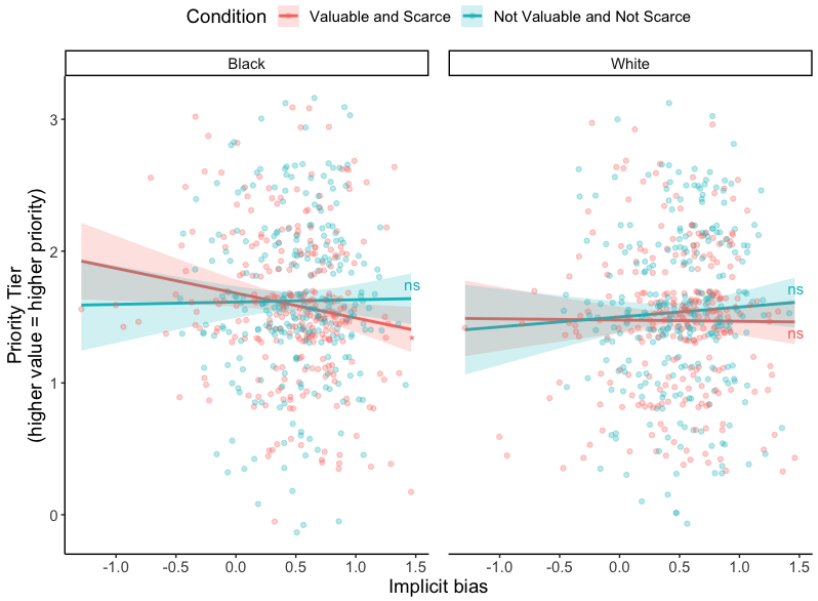
tiers (b = -0.085, SE = 0.063, p = 0.174, 95% CI [-0.209, 0.038]) but not associated with placement of White students (b = 0.033, SE = 0.062, p = 0.596, 95% CI [-0.089, 0.154]).

Critically, we found partial support for the opportunity hoarding hypothesis: the two-way interaction between implicit bias and race was primarily driven by the *Valuable and Scarce* condition. Although the three-way interaction of implicit bias, race, and condition did not reach significance (b = 0.122, SE = 0.109, p = 0.266, 95% CI [-0.093, 0.336]), the two-way interaction of implicit bias and race was significant only in the *Valuable and Scarce* condition (b = 0.179, SE = 0.071, p = 0.011, 95% CI [0.040, 0.318]). Unpacking this interaction revealed that greater implicit bias predicted placing Black students into lower priority tiers (b = -0.189, SE = 0.081, p = 0.021, 95% CI [-0.348, -0.029]) but not White students (b = -0.009, SE = 0.080, p = 0.906, 95% CI [-0.167, 0.148]). In contrast, in the *Not Valuable and Not Scarce* condition, the two-way interaction of implicit bias and race was not significant (b = 0.057, SE = 0.083, p = 0.490, 95% CI [-0.106, 0.221]), with implicit bias predicting neither Black (b = 0.018, SE = 0.096, p = 0.853, 95% CI [-0.170, 0.206]) nor White students' placement (b = 0.075, SE = 0.094, p = 0.426, 95% CI [-0.110, 0.261]; Figure 3.2).

Discussion

Replicating Study 1, White Americans' implicit bias again predicted biased decision-making. In this sample, this relationship was driven more strongly by implicit bias leading to placing Black students into lower priority tiers, rather than White students into higher tiers. Critically, this pattern emerged only when the opportunity was described as highly valuable and scarce, or "worth hoarding."

Figure 3.2. Associations between priority tier placement and implicit bias by student race (Black vs. White) and condition (Valuable and Scarce vs. Not Valuable and Not Scarce).



Note. Bias scores are raw values (i.e., zero indicates equal preference for Black and White individuals) and are displayed from the minimum to the maximum value in our data.

Study 3

Study 3 aimed to replicate and extend Study 2 by explicitly disentangling value and scarcity to clarify the critical condition under which implicit bias leads to biased decision-making. We tested three competing predictions: (1) the *Scarcity* hypothesis, proposing that implicit bias will lead to biased decisions when resources are scarce; (2) the *Value* hypothesis, that implicit bias will lead to biased decisions when resources are valuable; (3) the *Combination* hypothesis, that implicit bias will lead to biased decisions only when resources are both valuable and scarce. To distinguish among these predictions, we randomly assigned participants to one of the three conditions in which the AP program was described as either (1) valuable and scarce, (2) valuable but not scarce, or (3) scarce but not valuable. Under the *Scarcity* hypothesis, implicit bias would predict biased placement decisions (indicated by a significant interaction between

implicit bias and race) in the two scarce conditions; under the *Value* hypothesis, this interaction would occur in the two valuable conditions; and under the *Combination* hypothesis, it would occur only in the *Valuable and Scarce* condition.

Method

Participants

A total of 1,305 White participants were recruited from Prolific; among these, 1,239 completed the second part on time. Similar to previous studies, we excluded 30 participants who indicated careless responding on the IAT, two participants who did not answer the explicit bias questionnaires (feeling thermometers toward White and Black Americans), and 17 participants who indicated that they answered randomly at some point throughout the study. Additionally, we excluded 11 participants who identified themselves as Whites to Prolific's prescreening questions but did not identify as Whites to the demographic question in our survey.

In this study, we preregistered to exclude participants who did not pass the attention check (used in Study 2) or the manipulation check (described below). The exclusion rate did not differ significantly across experimental conditions (8.7% for the *Valuable and Scarce* condition, 13.0% for the *Valuable but Not Scarce* condition, 9.8% for the *Scarce but Not Valuable* condition; $\chi^2(2) = 4.34$, $p = 0.114$). After exclusion, the final sample included 1,055 participants, with 359 in the *Valuable and Scarce* condition, 347 in the *Valuable but Not Scarce* condition, and 349 in the *Scarce but Not Valuable* condition ($M_{age} = 42.6$, $SD_{age} = 13.3$; 43.0% men, 55.1% women). Post-hoc power calculations indicated that the final sample size gave 77% power to detect a same-sized interaction between implicit bias and student race observed in the *Valuable and Scarce* condition from Study 2.

Procedure

All procedures were largely similar to Study 2, except that participants were now randomly assigned to read a short paragraph describing AP courses as either (1) valuable and scarce, (2) valuable but not scarce, or (3) scarce but not valuable. We manipulated the value and scarcity the same way as in Study 2. For example, participants assigned to the *Scarce but Not Valuable* condition read that only 10% of students typically get into AP courses at this high school, but that contrary to common perceptions, students who take AP courses do not have a significant advantage in the college admission processes. Additionally, participants now completed manipulation check questions and mediator measures right after they read about the AP program but before they started reviewing the application materials.

Measures

The attention check (Part 1) and bias measures (Part 2) were identical to the previous studies.

Student Evaluation (Part 1). All measures were identical to the previous studies, except that the response options for the key question (priority tier decision) were modified to remove the reference to seats availability. Specifically, participants now indicated their tier placement by selecting one of the four options: 3 = *Should have the highest placement priority,* 2 = *Should be a top candidate to be placed, if possible,* 1 = *Could be placed,* 0 = *Should not be placed*.

Manipulation Check (Part 1). Participants answered one question assessing their understanding of how valuable AP courses are according to the information provided ("Does the description state that students who participate in the AP program have meaningful advantages in college admissions over those who do not?") by selecting one of the three options: *Yes, No, Does not say.* Participants also answered one question about how scarce such courses are ("According to the description, how many students can enroll in AP classes at this high school?") by selecting

one of the four options: *Very few, About half, Many, Does not say*. Those who did not select the correct answer for either the value (*Yes* for the *Valuable* conditions, *No* for the *Not Valuable* condition) or scarcity question (*Very few* for the *Scarce* conditions, *Many* for the *Not Scarce* condition) were asked to re-read the paragraph and answer the same questions again. Participants could try up to three times; those who answered incorrectly three times were allowed to proceed, but were considered as failing the manipulation check and excluded from the analyses. This decision was preregistered.

Analytic Strategy

Following established practice (e.g., Dovidio et al., 2002; Jacoby-Senghor et al., 2016), we preregistered to include both implicit and explicit bias in the same regression model if they were weakly correlated. The results from this model were generally consistent but weaker than those from models analyzing implicit and explicit bias separately, likely because each type of bias absorbs the other's explanatory power. For consistency with Studies 1 and 2, we report the results from the models analyzing implicit and explicit bias separately, but see *Appendix C* for the results from the combined model. We preregistered the two-way interaction between implicit bias and student race within each condition as the key term of interest, given that results from Study 2 indicated insufficient power to detect a significant three-way interaction of implicit bias, race, and experimental condition.

Results

Manipulation Check

The manipulation was successful at changing participants' perceptions of value of AP courses ($F(2, 1052) = 900.8$, $p < 0.001$). Post-hoc Tukey tests indicated that both *Valuable and Scarce* ($M = 4.64$, $SD = 0.61$) and *Valuable but Not Scarce* ($M = 4.75$, $SD = 0.53$) conditions

differed significantly from the *Scarce but Not Valuable* condition (M = 2.71, SD = 0.94, ps < 0.001), but not from each other (p = 0.121).

The manipulation was also successful at changing perceptions of scarcity of AP courses (F(2, 1052) = 1368, p < 0.001). Post-hoc Tukey tests indicated that both *Valuable and Scarce* (M = 4.38, SD = 0.77) and *Scarce but Not Valuable* (M = 4.41, SD = 0.83) conditions differed significantly from the *Valuable but Not Scarce* condition (M = 1.65, SD = 0.81, ps < 0.001), but not from each other (p = 0.865).

Balance Check

Randomization was successful, such that there was no significant differences across conditions in either implicit (*Valuable and Scarce*: M = 0.47, SD = 0.41; *Valuable but Not Scarce*: M = 0.49, SD = 0.40; *Scarce but Not Valuable*: M = 0.47, SD = 0.41; F(2, 1052) = 0.43, p = 0.651) or explicit bias (*Valuable and Scarce*: M = 0.31, SD = 2.02; *Valuable but Not Scarce*: M = 0.46, SD = 1.68; *Scarce but Not Valuable*: M = 0.27, SD = 1.99; F(2, 1052) = 1.02, p = 0.362).

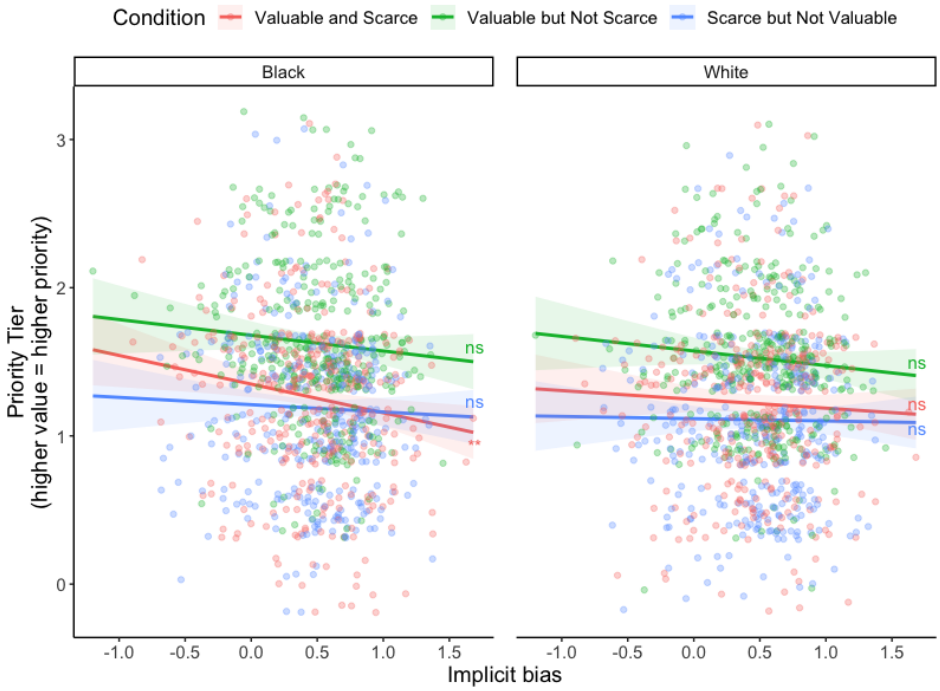
Main Analysis

The main effect of race was significant (b = -0.101, SE = 0.023, p < 0.001, 95% *CI* [-0.147, -0.056]), with White students placed into lower priority tiers than Black students. In this sample, the main effect of implicit bias was also significant (b = -0.087, SE = 0.037, p = 0.019, 95% *CI* [-0.160, -0.014]), indicating that on average, more implicitly biased participants placed students more stringently. Unlike in previous studies, the two-way interaction between implicit bias and race overall (i.e., across conditions) was not significant (b = 0.058, SE = 0.037, p = 0.115, 95% *CI* [-0.014, 0.131]).

Turning to our main question of whether this two-way interaction is qualified by experimental condition, we replicated Study 2 and found support for the *Combination* hypothesis. Specifically, a significant interaction between implicit bias and race was observed only in the *Valuable and Scarce* condition (b = 0.134, SE = 0.063, p = 0.032, 95% CI [0.012, 0.257]). Simple slope analyses showed that, as in the *Valuable and Scarce* condition in Study 2, greater implicit bias was associated with placing Black students into lower priority tiers (b = -0.193, SE = 0.071, p = 0.007, 95% CI [-0.333, -0.054]) but not White students (b = -0.059, SE = 0.069, p = 0.386, 95% CI [-0.194, 0.075]). In contrast, the interaction between implicit bias and race was close to zero in the *Valuable but Not Scarce* condition (b = 0.007, SE = 0.066, p = 0.913, 95% CI [-0.123, 0.137]), with implicit bias predicting neither Black (b = -0.106, SE = 0.076, p = 0.161, 95% CI [-0.254, 0.042]) nor White students' placement (b = -0.099, SE = 0.073, p = 0.175, 95% CI [-0.241, 0.044]). A similar pattern was observed for the *Scarce but Not Valuable* condition (interaction: b = 0.034, SE = 0.063, p = 0.594, 95% CI [-0.090, 0.158]), again with implicit bias predicting neither Black (b =-0.049, SE = 0.072, p = 0.496, 95% CI [-0.191, 0.092]) nor White students' placement (b = -0.015, SE = 0.070, p = 0.826, 95% CI [-0.152, 0.121]; Figure 3.3).

We also collected potential mediators to understand the psychological mechanisms through which value and/or scarcity moderates the relationship between implicit bias and biased decision-making. The mediator most relevant to the present findings was participants' anxiety about failing to secure admission to AP courses. In summary, although assignment to the *Valuable and Scarce* condition increased anxiety compared to the other two conditions, we found no evidence of mediation: Implicit bias did not predict biased decision-making at either high or low levels of anxiety (see *Appendix C* for details on measures, analytic strategy, and full results).

Figure 3.3. Associations between priority tier placement and implicit bias by student race (Black vs. White) and condition (Valuable and Scarce vs. Valuable but Not Scarce vs. Scarce but Not Valuable).



Note. Bias scores are raw values (i.e., zero indicates equal preference for Black and White individuals) and are displayed from the minimum to the maximum value in our data.

Discussion

Study 3 found that, consistent with the initial theorizing of opportunity hoarding, both scarcity and value of the contested opportunity are necessary conditions for implicit bias to yield biased decision-making. We replicated the key finding from Study 1 and the *Valuable and Scarce* condition from Study 2, showing that implicit bias predicted biased decisions only when both value and scarcity were present. Across Studies 2 and 3, this pattern was primarily driven by more implicitly biased individuals placing Black students into lower priority tiers.

General Discussion

The opportunity hoarding framework identifies race-based prejudice and stereotypes as key factors that sustain and reinforce inequalities in highly selective contexts. Across three

studies, we found evidence consistent with this hypothesis. White Americans' implicit pro-White/anti-Black bias predicted biased decision-making in the context of AP course placement (Studies 1-3); specifically, implicit bias predicted placing Black students into lower priority tiers, but not White students (Studies 2-3). Critically, this relationship only emerged when AP course participation was framed as a valuable *and* scarce opportunity, but not when either attribute was absent.

Our findings contribute to the implicit bias literature by identifying competition over valuable and scarce resources as one context that amplifies the effect of implicit bias on disparate outcomes. While the literature has established a small but robust relationship between implicit bias and intergroup discrimination (Kurdi et al., 2019; Oswald et al., 2013), these correlations are heterogeneous, underscoring the importance of identifying moderators. A growing body of work has shown that racial prejudice and discrimination become more pronounced in times of economic scarcity (Bianchi et al., 2018; Chattopadhyay & Bianchi, 2021), suggesting that scarcity may act as one potential moderator. However, these studies have rarely examined the simultaneous link between scarcity, bias, and discrimination, and their conceptualization and manipulation of scarcity has been broad—for example, inducing a general sense of scarcity through subconscious priming (e.g., Krosch & Amodio, 2014) or varying the proportion of resources available to the self out of a larger total (e.g., Berkebile-Weinberg et al., 2022; Krosch et al., 2017). Our work extends this work and demonstrates that the specific type of scarcity also matters: When an opportunity is not particularly valuable, implicit bias does not result in less favorable treatment of Black people, even if the opportunity is scarce.

There are several reasons why both value and scarcity are necessary for implicit bias to predict biased decision-making. Valuable and scarce opportunities may uniquely induce anxiety about not securing them (Roda & Wells, 2013; Sattin-Bajaj & Roda, 2020), unlike opportunities

that are valuable but abundant (which are easier to obtain) or scarce but low-value (which carry lower stakes). Similarly, resource competition heightens intergroup threat (Sherif, 1966), and this effect may be amplified when the competition involves opportunities that are both difficult to obtain and significantly enhance group status once secured. Together, heightened anxiety and perceived threat may motivate White Americans to act in line with their implicit biases, denying outgroup members access to these resources. Our exploratory mediation analysis in Study 3 did not find evidence of mediation by either anxiety or intergroup threat (see *Appendix C*). However, future research could explore these possibilities using alternative measures of anxiety and intergroup threat. The role of these factors may also be more pronounced when outcomes are directly relevant to the self. In the present research, participants acted as third parties making decisions for students whose outcomes would not affect them personally. Future studies could manipulate the extent to which participants imagine their *own* child's chances of securing valuable and scarce opportunities are at risk, and assess their willingness to engage in behaviors that influence third-party decisions to benefit their child (and ingroup members broadly)—an approach more aligned with qualitative work on opportunity hoarding (e.g., White, middle-class parents prodding teachers to place their children in advanced tracks; Lewis & Diamond, 2015).

In addition to clarifying the psychological mechanism linking implicit bias to biased decision-making (and opportunity hoarding more broadly), future work should examine these phenomena in more ecologically valid settings, especially given that our experimental findings did not fully mirror real-world disparities. In real-world, biased decision-making is manifested as overrepresentation of White over Black students in AP classrooms. However, across our studies, Black students were consistently placed into higher priority tiers than equally qualified White students. While the relationship between implicit bias and placement decisions observed in our studies (i.e., greater implicit bias linked to deprioritizing Black students) aligned with theoretical

predictions, future work should test this relationship in more naturalistic settings. For example, data permitting, more granular analyses examining public high school students' actual AP participation rates by subject would enable a more ecologically valid test of the opportunity hoarding hypothesis—for example, assessing whether this pattern is more pronounced in subjects perceived as more valuable (e.g., AP Computer Science versus AP Geography). Future research may also explore whether similar patterns emerge in other contexts, such as competition for highly coveted but limited job opportunities.

Addressing disparities in social mobility requires closing excellence gaps; closing excellence gaps requires ensuring that all students have equal opportunities to realize and develop their full potential. However, the very valuable and scarce nature of these opportunities may reduce motivation to regulate biases, reinforcing the link between implicit bias and disparate outcomes. Efforts to address the underrepresentation of stigmatized students in AP classrooms and other pathways to excellence should consider strategies to minimize the effect of implicit bias in decisions about who deserves access to these opportunities.

General Discussion

This dissertation examined if and when racial bias contributes to disparities in advanced educational opportunities, with a focus on the Advanced Placement (AP) program. Using multiple levels of analysis (from regional to individual) and a range of methods (archival data analyses to experimental studies), the findings offer a nuanced understanding of the relationship between racial bias and AP participation disparities. Drawing on multiple large, publicly available datasets, Chapter 1 found that county-level pro-White/anti-Black implicit and explicit bias was consistently associated with greater Black-White disparities in AP course enrollment. This pattern did not hold for subsequent AP exam taking and passing, suggesting that bias primarily manifests during the identification and selection process. Importantly, the relationship between bias and enrollment disparities was partially explained by teachers' biases, over and above structural (concentration of AP courses in predominantly White schools) and developmental factors (racial achievement gaps prior to high school). These findings hint that teacher bias may shape interpersonal dynamics between teachers and students—for example, by leading teachers to evaluate similarly qualified Black and White students differently or behave in ways that discourage Black students from enrolling in AP courses. Chapter 2 directly tested the differential evaluation hypothesis, examining whether teachers' implicit and explicit racial bias predicted their AP placement decisions differently for Black versus White students. A pilot experiment with broadly defined teachers provided preliminary evidence: Greater implicit and explicit bias predicted placing Black students into lower priority tiers, but not White students. However, two larger experiments with White, public high school teachers found no such evidence; implicit and explicit bias were either associated with less favorable placement decisions for both groups or unrelated to placement decisions altogether. Finally, Chapter 3

investigated the types of opportunities where implicit bias is most likely to shape race-based evaluations. Implicit bias predicted placing Black students into lower priority tiers only when AP participation was framed as a highly valuable and scarce opportunity, but not when either value, scarcity, or both were absent. While more work is needed to unpack the mechanism, one possibility is that competition over valuable and scarce opportunities heightens anxiety and intergroup threat, reducing motivation to regulate implicit biases.

Limitations

While the present work (in particular, Chapter 1) suggests that implicit bias shapes AP participation disparities primarily through interpersonal routes, the specific processes involved are not yet fully understood. Chapter 2 has not offered strong evidence that teachers' biases directly influence placement decisions (at least within our experimental paradigm). Chapter 3 points to the valuable and scarce nature of certain opportunities as contextual factors that may amplify the influence of implicit bias, but the psychological mechanisms driving this effect need to be further investigated. Additionally, findings across chapters suggest that bias primarily influences outcomes for Black students more than for White students. While this pattern aligns with meta-analytic findings showing that IAT scores correlate more strongly with behaviors involving Black targets than White targets (Oswald et al., 2013), the reasons behind this asymmetry remain unclear.

Moreover, it is noteworthy that the findings from the experimental studies in Chapters 2 and 3 do not perfectly mirror the results of the archival analyses in Chapter 1. Specifically, across experiments, Black students were consistently placed into higher priority tiers than equally qualified White students. This led to a counterintuitive interpretation of the interaction between participant bias and student race: Less implicitly biased individuals showed greater

preferences for Black students, and more biased individuals showed no preferences (rather than more biased individuals showing greater preferences for White students, and less biased individuals showing no preferences). One potential explanation is social desirability concerns; even strongly biased participants may have been motivated to suppress their preferences for White students, in favor of appearing unbiased. Alternatively, less biased participants may be especially attuned to the persistent underrepresentation of Black students in AP courses and may have intentionally adjusted their evaluations to correct for this disparity, whereas more biased participants did not engage in such compensatory efforts. While the present studies cannot disentangle these explanations, they underscore the need for future research examining placement decision processes in more ecologically valid settings (where decision-makers might be less influenced by social desirability concerns), as well as alternative interpersonal mechanisms through which bias contributes to unequal outcomes.

Future Research

The current work presents multiple opportunities for future research. First, identifying the various actors within school environments and examining how their biases shape student outcomes can be extended to incorporate additional agents and their interactions. For example, future research could explore how White peers' racial biases discourage Black students from enrolling in predominantly White AP classrooms. Growing up in biased communities, White children may internalize racial biases, adopting the belief that having Black peers in their schools and classrooms would somehow lower the quality of education they receive (Hagerman, 2021, p. 209). Their biases, in turn, may manifest as microaggressions in their interactions with Black peers—such as questioning their intellectual abilities or dismissing their contributions—creating an unwelcoming climate that places an additional burden to Black students (J. A. Lewis et al.,

2021; Taliaferro & DeCuir-Gunby, 2008). Future work should also examine how different agents' biases may interact to influence student enrollment outcomes. As documented in the opportunity hoarding literature, White, middle-class parents' hoarding of educational resources often involve close communications with school administrators (Murray et al., 2019) and teachers (A. E. Lewis & Diamond, 2015). Understanding the interplay between parents and teachers—for example, whether and under which circumstances teachers can offset parents' bias—would provide a more accurate reflection of the complex, real-world dynamics that shape AP enrollment decisions.

Second, while the current work focused on the implicit biases of White Americans, future research may also examine the biases of non-White individuals. On the one hand, Project Implicit data show that Black individuals, on average, exhibit no implicit racial preference (average IAT D-score = -0.05), and Hispanic individuals show pro-White implicit bias (D-score = 0.25) but to a lesser extent than White individuals (D-score = 0.36). Research on demographic matching further suggests that students of color, particularly Black students, benefit academically from having same-race teachers (Redding, 2019). These findings imply that in contexts with more Black or other low-status racial minority teachers, bias—and consequently, bias-driven disparities in access to AP and other advanced academic opportunities—may be reduced. On the other hand, some evidence suggests that teachers of stigmatized groups also hold higher expectations for majority group members. For example, one experimental study found that non-White teachers (predominantly Black and Latinx) rated White students' math ability higher than that of Black and Latinx students, despite identical work quality (Copur-Gencturk et al., 2020). Similarly, albeit in the domain of gender, female teachers were more likely than male teachers to underrate girls' mathematical ability (Robinson-Cimpian et al., 2014). These findings raise the

possibility that not only White teachers' biases but also those of non-White teachers may contribute to disparities in AP participation and beyond. This possibility could not be directly examined in Chapter 1 due to the limited number of non-White teachers in the Project Implicit dataset, but remains an important avenue for future research.

Third, it remains an open question whether the dynamics observed in this dissertation extend beyond Black-White dynamics. One particularly relevant group to examine is Asians, who are often equally or even better represented in AP classrooms than their White peers (Chatterji et al., 2021). Unlike Black students, Asian students are often stereotyped as high-achieving, hardworking, and academically driven (Lee & Zhou, 2015). These "model minority" stereotypes make it difficult to apply cultural explanations used to justify Black underrepresentation (e.g., lack of intelligence or commitment to education). Accordingly, even among individuals who harbor anti-Asian biases or stereotypes (e.g., associating Asians with foreignness; Zhou, 2004; Zou & Cheryan, 2017), such biases may not necessarily lead to excluding Asian students from advanced academic opportunities. Rather, they may more reliably predict exclusion of Asian students from non-academic domains, such as extracurricular or leadership opportunities, where stereotypes of Asians as non-assertive may be used to justify their exclusions (Sy et al., 2017). These effects may also vary across subgroups (e.g., East vs. South Asians; Lu et al., 2020), highlighting the need for a nuanced exploration of how biases and stereotypes associated with different minority groups shape their outcomes. Relatedly, while this dissertation focused on AP courses and educational opportunities more broadly, future research should examine how bias contributes to disparities in other high-stakes domains, such as employment, promotion, and leadership opportunities. For example, the findings from Chapter 3 suggest that bias operates most strongly when opportunities are valuable and scarce, which may

help explain why gender and racial disparities in leadership representation become more pronounced at higher organizational levels (Bailes & Guthery, 2020; Krivkovich et al., 2025).

Methodologically, the current work focused on pro-White/anti-Black *attitudes* measured via White-Good/Black-Bad IAT (for implicit bias) and feeling thermometers (for explicit bias). Prior research has highlighted race-based *beliefs*, i.e., stereotypes, as key mechanisms for justifying and legitimizing the status quo (Berkebile-Weinberg et al., 2022; Diamond & Lewis, 2022; Fiske et al., 2002), raising the question of whether measures of academic race stereotypes might more strongly predict enrollment disparities. While meta-analytic findings provide weak support for this hypothesis—explicit attitudes have been found to correlate more strongly with behaviors than explicit stereotypes, and implicit attitudes correlated with behaviors to a similar extent as implicit stereotypes (Kurdi et al., 2019; Talaska et al., 2008)—future research could empirically address this possibility. Additionally, an individual IAT score has been criticized as an unreliable measure of stable individual difference. A meta-analytic test-retest reliability estimate of race IAT is 0.49, indicating that approximately half of the variability in IAT scores stems from measurement error and contextual factors rather than stable, individual-level implicit attitudes (Lai & Wilson, 2021). This unreliability may help explain why teachers' biases predicted greater Black-White AP enrollment disparities at the county level (Chapter 1), but not at the individual level (Chapter 2). Aggregating individual IAT responses at the regional level helps cancel out measurement error and captures biases that are shared within a given region, activated in part by common contextual cues (e.g., the presence of Confederate monuments in public spaces; Calanchini et al., 2022; Payne et al., 2017; Vuletich & Payne, 2019). Future work may replicate the studies in this dissertation by having participants complete multiple IATs and

applying statistical techniques such as latent aggregation (Carpenter et al., 2023) to derive more reliable individual-level estimates of implicit bias.

Practical Implications

Knowing if and when bias matters is one thing; knowing how to fix it is another. If anything, prior research suggests that prejudice, particularly implicit prejudice, can be reduced but not as easily as one may hope for (Paluck et al., 2021). Most interventions aimed at shifting implicit attitudes rely on brief, single-session manipulations, and while some produce short-term changes, the effects are often small (Forscher et al., 2019) and not durable (Lai et al., 2016). These findings suggest that rather than trying to eliminate individual biases, a more effective approach may be to change the *environment* to minimize their influences. From this perspective, understanding when bias matters become critical, as these insights can inform targeted interventions. This dissertation demonstrates that bias is most impactful at the enrollment stage for high-stakes, scarce opportunities, suggesting that interventions should focus on reducing subjectivity in the process for identifying and selecting students for these opportunities.

One way to reduce subjectivity is through automatic enrollment policies, which place students who demonstrated proficiency in advanced courses unless they opt out. This approach minimizes the role of interpersonal biases, such as teachers selectively encouraging students from certain groups to enroll while overlooking others (Witenko et al., 2017). There is some evidence that automatic enrollment increases the representation of underrepresented students in advanced coursework. For example, Card and Giuliano (2016) examined the effects of universal screening in a large Florida school district. Previously, only students referred by teachers or parents could take a test to determine gifted eligibility; the district replaced this system with universal screening, requiring all second graders to complete the test. This change increased the

odds of being identified as gifted by 74% for Black students and 118% for Hispanic students. Similarly, across 72 districts in Washington, academic acceleration policies—which placed students into advanced courses based on statewide standardized test scores—boosted enrollment for all students but had a greater impact for underrepresented minority students (Austin et al., 2025). Although using standardized test scores alone would not ensure equal representation of White and URM students (given persistent racial gaps in test performance; Reardon et al., 2019), test scores are less susceptible to interpersonal biases than other performance measures involving subjective judgments, such as teacher recommendations or grades. Indeed, findings from these studies suggest that automatic enrollment based on standardized test performance may help mitigate the influence of interpersonal bias in shaping access to advanced coursework.

In cases where automatic enrollment is not an option, schools could still benefit from employing clear, standardized selection criteria. Quinn (2020) found that teachers rated a writing sample as lower quality when they believed it was written by a Black student rather than a White student when using a vaguely defined rubric (e.g., one that did not specify evaluation domains); however, when teachers used a clearly defined rubric that outlined specific evaluation domains, this bias disappeared. Similarly, Copur-Gencturk and colleagues (2020) found that teachers showed no bias when assessing the correctness of a specific math problem solution, but exhibited bias against Black students when making more generalized judgments about their overall mathematical ability. In the context of AP, even if schools choose to have additional requirements for selecting students into advanced opportunities—such as a sample essay—they may reduce the role of teacher bias by establishing clear, well-defined criteria that prevent shifting standards from being used to justify discrimination (Uhlmann & Cohen, 2005).

Beyond standardization, accountability mechanisms may further reduce bias in selection decisions. The accountability literature theorizes that when people feel accountable, they are more likely to think deliberately, consider all evidence, and avoid relying on cognitive biases and heuristics (Lerner & Tetlock, 1999). Indeed, when majority group members (as defined by the minimal group paradigm) were expected to explain their allocation decisions to outgroup members, they made fairer allocations than when no such explanation was required (Dobbs & Crano, 2001). Applying similar strategies, such as requiring decision-makers to justify their AP placement decisions, may reduce reliance on racial biases and help mitigate disparities in enrollment outcomes.

Last but not least, this work calls for more rigorous, detailed data on the policies schools use to identify and select students for advanced learning opportunities. Districts and schools vary widely in their selection criteria, and even when standardized policies exist—as in the earlier example of Washington's academic acceleration policy—implementation can differ significantly. Some schools may follow the intended model, using only standardized test scores, while others may still consider additional measures like prior grades, scores on other tests, and teacher recommendations (Austin et al., 2025). Currently, the Civil Rights Data Collection (CRDC) asks schools whether students can enroll in all AP courses via self-selection, defined as student being able to enroll "without needing a recommendation or without meeting other criteria, except for any necessary course prerequisites." However, qualitative data that we collected from over 100 school principals revealed substantial discrepancies in their CRDC responses versus our survey, with 47% of principals providing contradictory answers—either reporting self-selection in the CRDC but not in our survey, or vice versa. These inconsistencies may stem from policy changes over time (i.e., between when they completed the CRDC and our survey), differences across

subjects (e.g., self-selection allowed for AP English Literature but not AP Calculus), or misinterpretations of the CRDC question (e.g., viewing minimum GPA requirements as part of "necessary course prerequisites"). Regardless, more nuanced data on school policies is essential for understanding the conditions under which interpersonal racial bias operates more or less powerfully. This, in turn, would enable developing more concrete interventions targeting the relevant psychological mechanism underlying these disparities.

Conclusion

In closing, this work speaks to the importance of understanding the role of racial bias in shaping disparities in opportunities to develop and demonstrate excellence. It contributes to the growing research on racial excellence and opportunity gaps (Karna et al., 2025; Meyer et al., 2024) and extends the implicit bias literature by demonstrating the direct link between implicit bias and opportunity gaps, as well as identifying contextual moderators that strengthen this link. Practically, these findings are particularly relevant in the current political climate, where majority group members often attribute missed opportunities to DEI initiatives (Borchers, 2025) and efforts to promote diversity in schools and organizations face mounting backlash (Goldberg, 2025; Otterman et al., 2025). If anything, this work demonstrates that racial biases prevailing in our society limit Black individuals' opportunities to demonstrate excellence, making efforts to minimize their impact more crucial than ever.

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Data Preparation

Grades 9-12 Enrollment

As described in the main text, CRDC does not collect information about enrollment by grade. This would result in underestimation of the probability of AP course enrollment among schools that offer 8th grade and below, as AP courses are offered only for students in 9th-12th grades. We followed prior work (Xu et al., 2021) and used the Common Core Data (CCD) to impute by-grade enrollment. Specifically, for each wave of the CRDC data, we first matched it with the corresponding wave of the CCD data, using the 12-digits unique school identifiers. Approximately 4.3% of the schools were not matched this way ($N_{2013\text{-}14}$ = 535 schools; $N_{2015\text{-}16}$ = 537 schools; $N_{2017\text{-}18}$ = 664 schools). We used additional information (i.e., combination of school name and state) to match the remaining schools. This left approximately 1.1% of schools left unmatched ($N_{2013\text{-}14}$ = 126 schools; $N_{2015\text{-}16}$ = 113 schools; $N_{2017\text{-}18}$ = 196 schools), which were excluded from our analyses.

For the schools that were matched ($N_{2013\text{-}14}$ = 12,981 schools; $N_{2015\text{-}16}$ = 13,308 schools; $N_{2017\text{-}18}$ = 13,613 schools), we identified only schools that offer 8th grade and below, as there is no need to correct enrollment for schools that offer 9th-12th grades only. This left approximately 19.0% of schools that need to be corrected ($N_{2013\text{-}14}$ = 2,396 schools; $N_{2015\text{-}16}$ = 2,573 schools; $N_{2017\text{-}18}$ = 2,625 schools). If the total CCD enrollment was within +/- 5 percent of the total CRDC enrollment, we used the CCD 9th-12th grades enrollment data. If not, we used the CCD data to calculate the ratio of 9th-12th grades enrollment to the total enrollment and applied this ratio to the CRDC total enrollment to estimate the number of students in 9th-12th grades.

Covariates

Following prior work (Riddle & Sinclair, 2019), we included the following covariates in the models estimating county-level explicit and implicit bias (poststratification models) as well as the models estimating Black-White gaps in AP participation rates (main models). We used state-level variables for the poststratification models, and county-level variables for the main models. All variables were taken from the American Community Survey (ACS) 5-year estimates for the time period ending in the year the CRDC data was collected.

Population size and proportions included the total population, the proportion of White people, the proportion of Black people, and the ratio of White-to-Black people (ACS Table B02001).

Socioeconomic indicators included the proportion of unemployed people aged 16 or over (ACS Table S2301), proportion of families and people whose income was below the poverty line (ACS Table S1701), proportion of people with a Bachelor's degree or higher (ACS Table S1501), and the median income (ACS Table S1903). For the main model, we also included the estimates of *difference* between Blacks and Whites for each of these variables; the same ACS tables were used, except for the proportion of White and Black people with a Bachelor's degree or higher (ACS Tables C15002A and C15002B, respectively).

Urban-rural indicator was operationalized as housing density per square mile of land area (Census Table GCT-PHI).

Mobility was operationalized as the proportion of people who moved from different state or abroad (for state-level variable), or the proportion of people who moved from different county, state or abroad (for county-level variable; ACS Table S0701).

Segregation was operationalized as dissimilarity index (Massey & Denton, 1988), reflecting the proportion of Black people that would need to move to different geographical areas (tract or county) to achieve even distribution of Black-White population across the larger unit (county or state; calculated using the information obtained from ACS Table B02001).

Post-Stratified Bias Estimates

We used multilevel regression and post-stratification (Hoover & Dehghani, 2020) to get more accurate estimates of county-level residents' implicit and explicit bias. Specifically, we post-stratified on age to match the age distribution of Project Implicit data to the actual age distribution of the county. We first grouped participants into five age groups (15-24, 25-34, 35-54, 55-74, 75 or older). Next, for each type of bias (implicit or explicit), we ran a multilevel model estimating bias scores from Project Implicit as a function of state-level covariates, with random intercepts by state, county, and age group. From this model, we derived the model-predicted bias scores for each age group in each county in each state. Finally, we computed the average of bias scores for each county, weighted by the number of White people in each age group in a given county using data obtained from the American Community Survey (ACS). For example, if a given county had a higher proportion of White residents aged between 25-34, the procedure will give a greater weight to the model-predicted bias score of this age group to accurately reflect the age distribution of the county.

For estimating county-level teachers' implicit and explicit bias, we followed the same procedure but used different age categories (18-29, 30-49, 50-54, 55 or older) to align with the National Teacher and Principal Survey (NTPS; formerly the Schools and Staffing Survey), which reports public school teachers' age distributions using these categories. Additionally, because NTPS provides only state-level data—without disaggregating by county or race—our post-stratification assumes that the age distribution of White teachers mirrors that of all teachers and remains uniform across counties within the same state. We retrieved two available NTPS data, from the 2011-12 and 2017-18 academic years, and selected the data closest to the CRDC

data collection period for post-stratification (i.e., 2011-12 NTPS data for the 2013-14 CRDC analysis, and 2017-18 NTPS data for the 2015-16 and 2017-18 CRDC analyses).

Sample Sizes

As described in the main text, our analytic sample includes only schools with a sufficient number of Black and White students to calculate Black-White AP participation gaps. Specifically, we retained schools with at least 10 Black and 10 White students enrolled in grades 9-12 (for AP course enrolment gaps), at least 10 Black and 10 White students enrolled in at least one AP course (for AP exam taking gaps), and at least 10 Black and 10 White students who took at least one AP exam (for AP exam passing gaps). See Table A1 for the number of schools and counties retained in the analytic sample for each year and outcome.

Table A1. Number of schools and counties in the analytic sample.

	2013-14 AY	2015-16 AY	2017-18 AY
Course Enrollment			
Number of schools	8,367	8,565	8,528
Number of counties	1,720	1,728	1,667
Exam Taking			
Number of schools	3,718	3,993	3,859
Number of counties	851	863	822
Exam Passing			
Number of schools	1,970	2,298	-
Number of counties	484	529	-

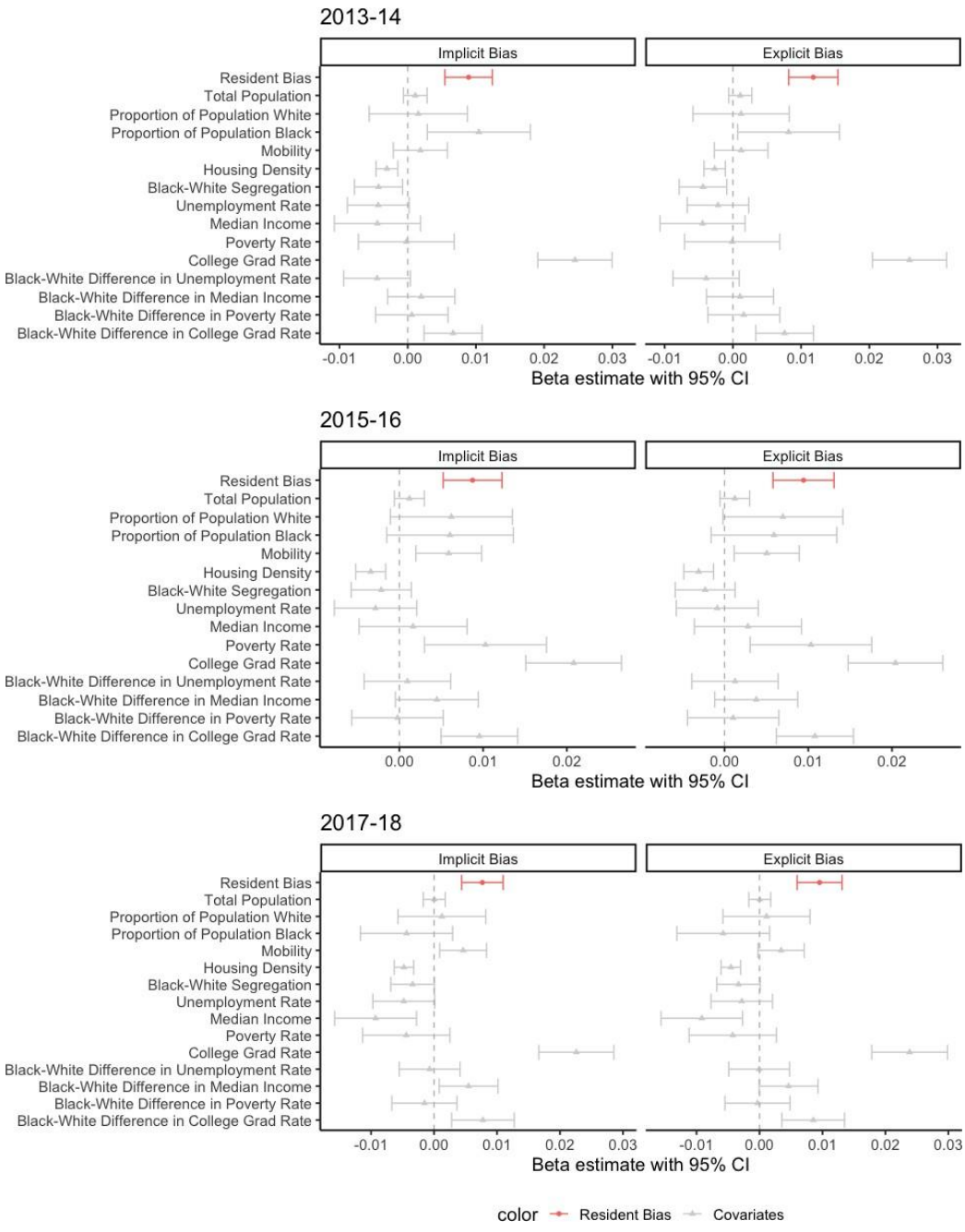
Main Analyses

AP Course Enrollment

As reported in the main text, residents' implicit and explicit bias consistently predicted greater Black-White gaps in AP course enrollment rates (Figure A1). Follow-up analyses revealed that this was driven primarily by greater implicit and explicit bias predicting lower enrollment rates for Black students (Figure A2) but not White students (Figure A3).

Black-White Exam Taking Rate Gap

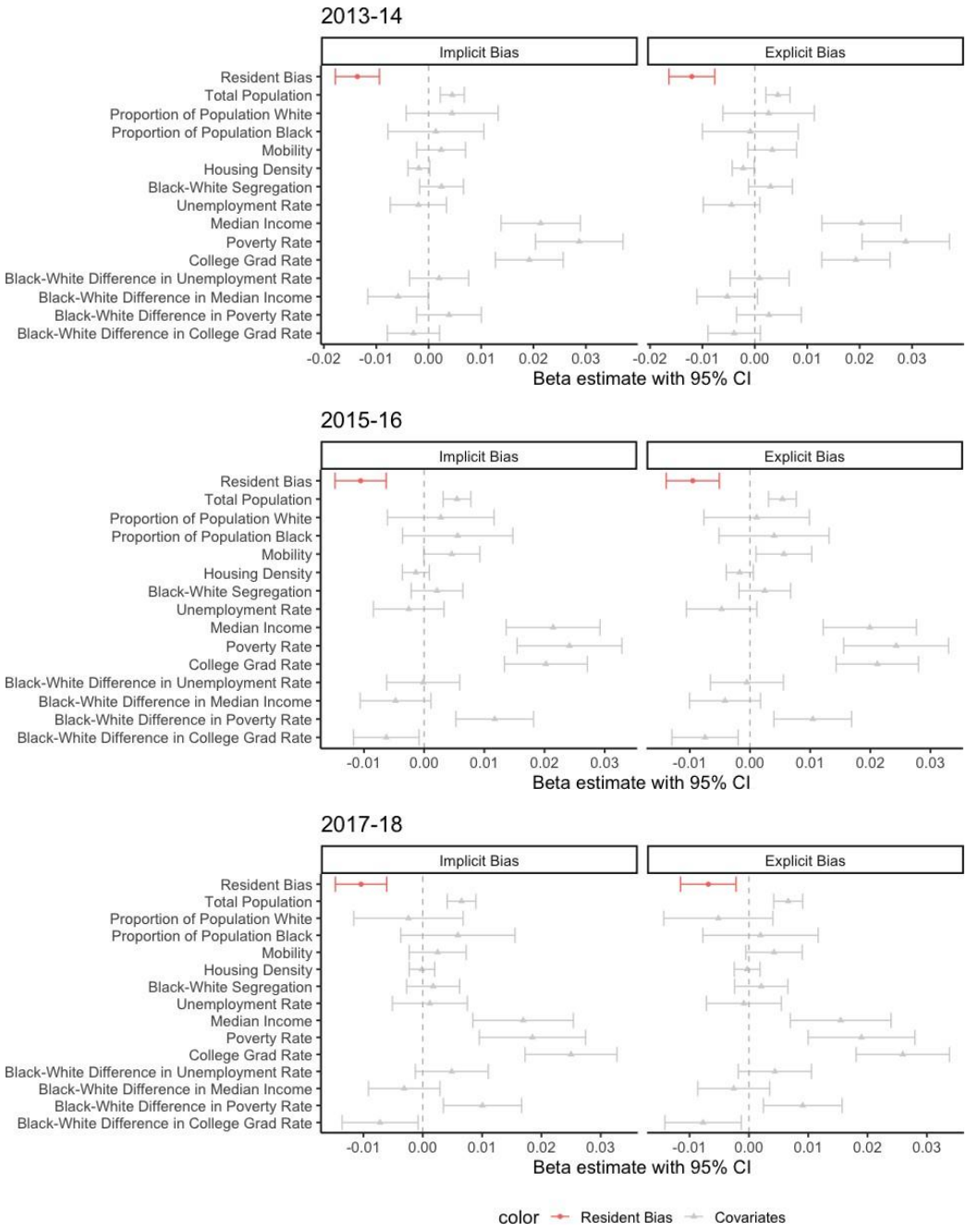
Figure A1. Coefficient estimates of key predictors (residents' implicit and explicit bias) and county-level covariates predicting Black-White gaps in AP course enrollment rates.



Note. All variables were standardized prior to estimation for comparability. Bars represent 95% confidence intervals.

Black Enrollment Rate

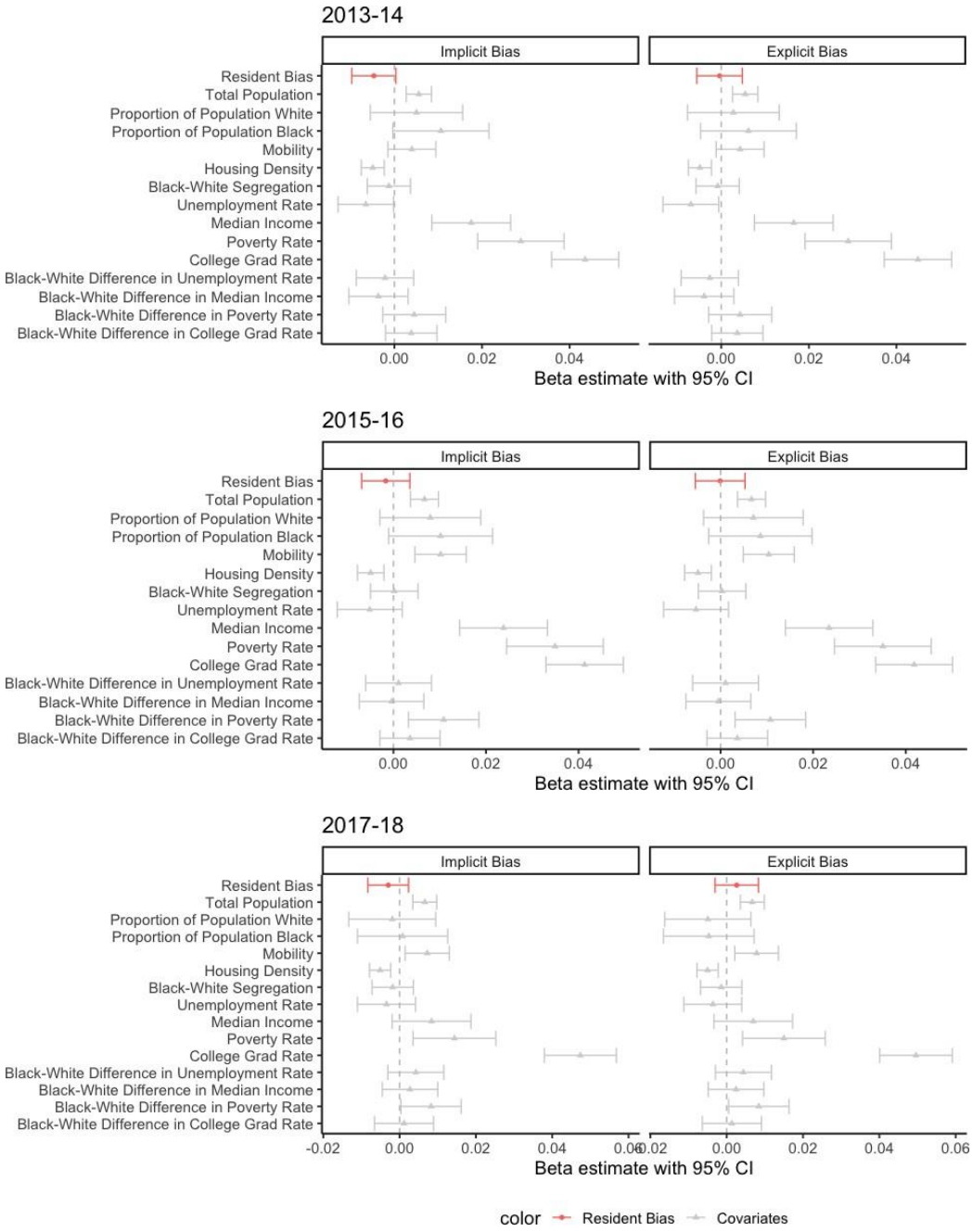
Figure A2. Coefficient estimates of key predictors (residents' implicit and explicit bias) and county-level covariates predicting AP course enrollment rates for Black students.



Note. All variables were standardized prior to estimation for comparability. Bars represent 95% confidence intervals.

White Enrollment Rate

Figure A3. Coefficient estimates of key predictors (residents' implicit and explicit bias) and county-level covariates predicting AP course enrollment rates for White students.



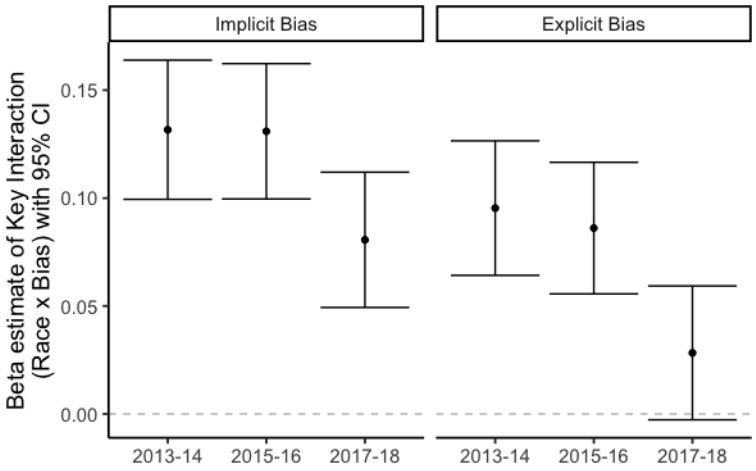
Note. All variables were standardized prior to estimation for comparability. Bars represent 95% confidence intervals.

Robustness Check: Binomial Regression

We initially preregistered multilevel binomial regressions, modeling the likelihood of participating in the AP program. For example, for the enrollment gap analysis, the number of Black (White) students enrolled in AP courses ("successes") and not enrolled ("failures," obtained by subtracting the number of successes from the number of Black (White) students in grades 9-12) were entered as the outcome, and racial group (0 = Black, 1 = White), county-level bias, and their interaction were entered as predictors. In this model, a positive and significant interaction of race and bias would indicate larger AP participation gaps in more biased counties. We deviated from this model in favor of the current model reported in the main text, which uses participation gaps as the outcome and estimates the main effect of bias, for interpretability and consistency with the mediation analysis.

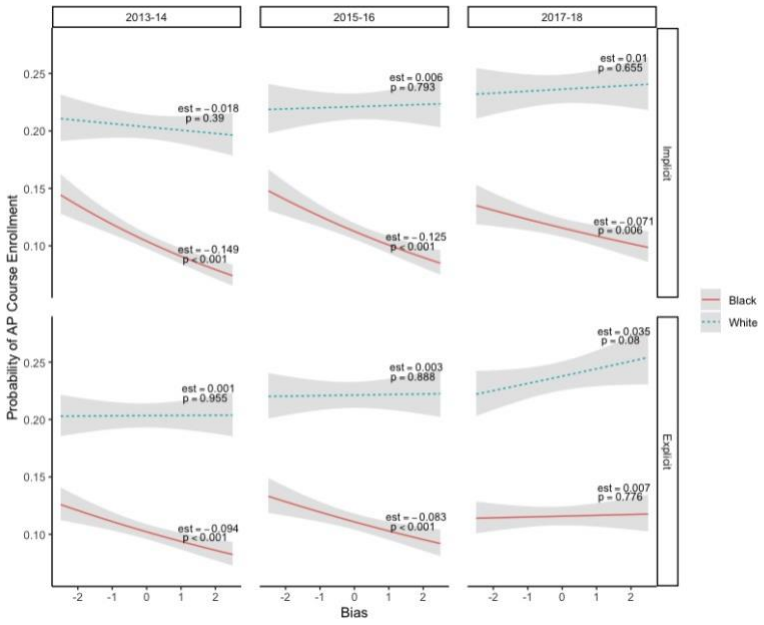
Overall, the results for the binomial regression aligned with those reported in the main text. The interaction between race and bias was consistently positive and significant, except for explicit bias in 2017-18 ($p = 0.074$; Figure A4). This interaction was driven by bias predicting a lower probability of enrollment for Black students, but not for White students (Figure A5).

Figure A4. Coefficient estimates of the key predictor (interaction between race and bias) predicting the probability of AP course enrollment.



Note. Bars represent 95% confidence intervals.

Figure A5. Simple slopes of bias on the probability of AP course enrollment for Black versus White students.



Note. Bands represent corresponding 95% confidence intervals; *est* represents the estimate of the simple slope; *p* represents p-value indicating whether the slope is significantly different from zero.

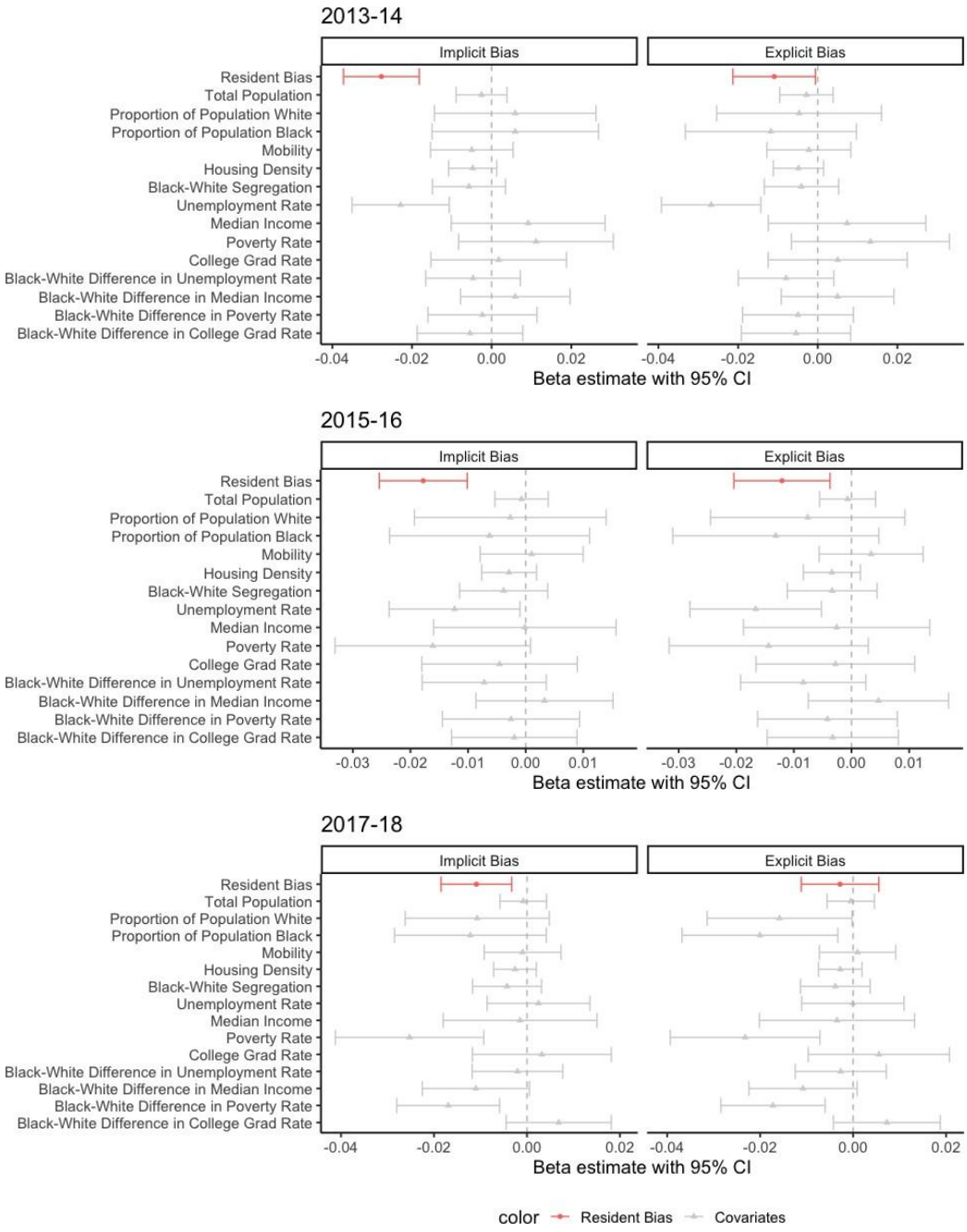
AP Exam Taking

As reported in the main text, residents' implicit and explicit bias consistently predicted *smaller* Black-White gaps in AP exam taking rates, with the exception of explicit bias in 2017-18 (Figure A6). For implicit bias, this was driven by implicit bias generally predicting higher exam taking rates for both Black (Figure A7) and White students (Figure A8), but more strongly and consistently for Black students. For explicit bias, explicit bias generally did not predict exam taking rates when examining Black and White students separately (Figure A7-8).

A weaker but similar pattern emerged in the binomial regressions. Specifically, although point estimates of the key interaction (race and bias) were consistently negative—indicating *smaller* differences in the probability of taking AP exams in more biased counties—the estimates were not significantly different from zero, with the exception of implicit bias in 2013-14 (p = 0.006; Figure A9). Nonetheless, the overall conclusion remains unchanged: Bias acts more critically at the point of selection, such that in more biased counties, sufficiently qualified Black students are potentially overlooked from consideration.

Black-White Exam Taking Rate Gap

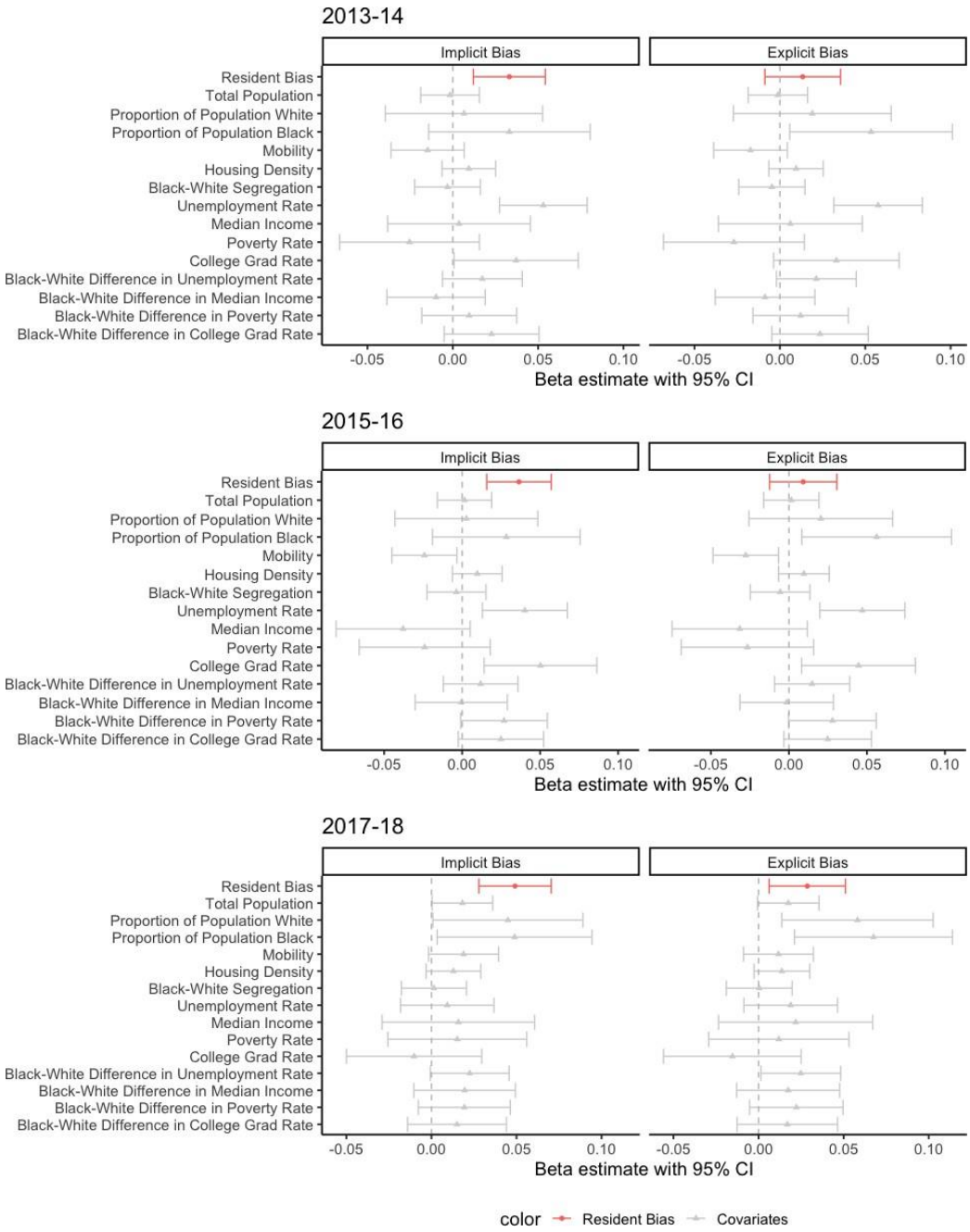
Figure A6. Coefficient estimates of key predictors (residents' implicit and explicit bias) and county-level covariates predicting Black-White gaps in AP exam taking rates.



Note. All variables were standardized prior to estimation for comparability. Bars represent 95% confidence intervals.

Black Exam Taking Rate

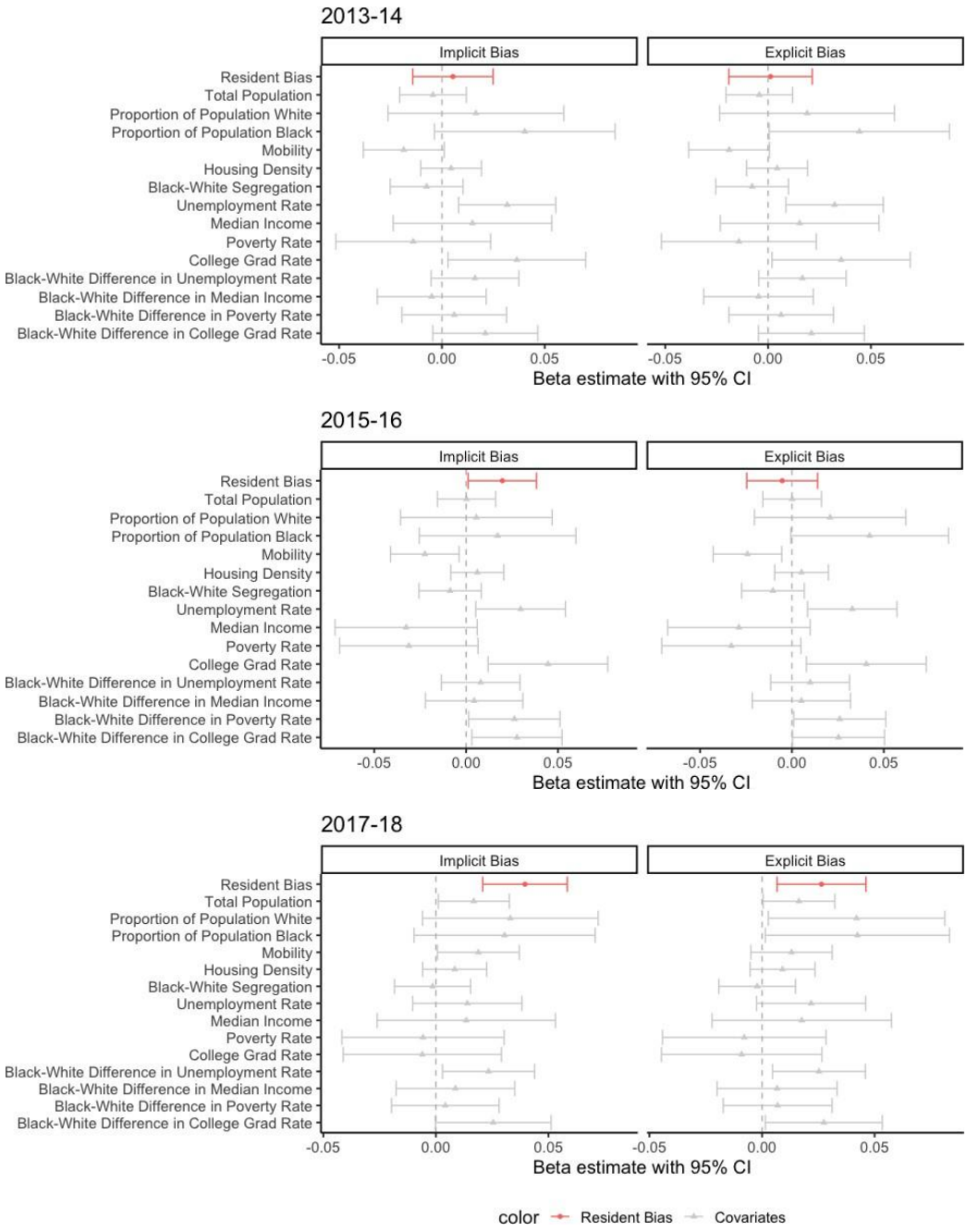
Figure A7. Coefficient estimates of key predictors (residents' implicit and explicit bias) and county-level covariates predicting AP exam taking rates for Black students.



Note. All variables were standardized prior to estimation for comparability. Bars represent 95% confidence intervals.

White Exam Taking Rate

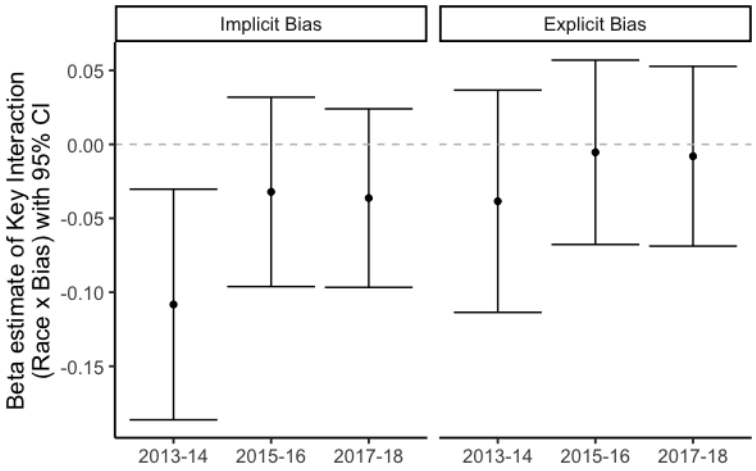
Figure A8. Coefficient estimates of key predictors (residents' implicit and explicit bias) and county-level covariates predicting AP exam taking rates for White students.



Note. All variables were standardized prior to estimation for comparability. Bars represent 95% confidence intervals.

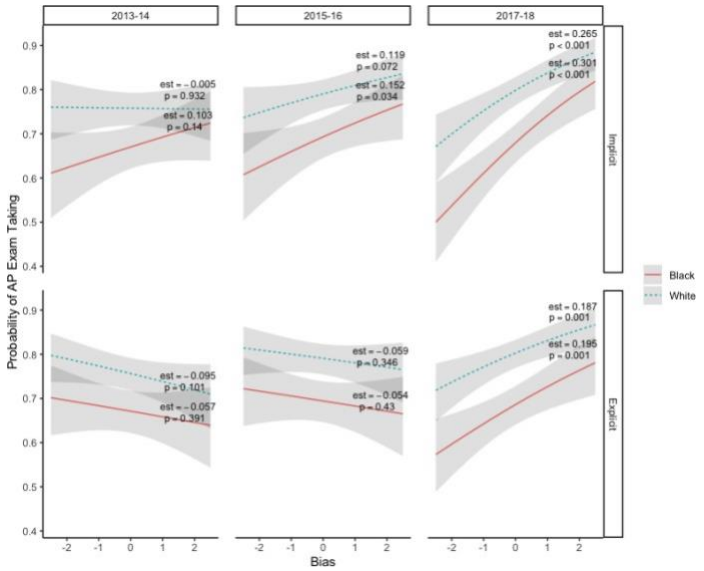
Robustness Check: Binomial Regression

Figure A9. Coefficient estimates of the key predictor (interaction between race and bias) predicting the probability of taking AP exam.



Note. Bars represent 95% confidence intervals.

Figure A10. Simple slopes of bias on the probability of AP exam taking for Black versus White students.



Note. Bands represent corresponding 95% confidence intervals; *est* represents the estimate of the simple slope; *p* represents p-value indicating whether the slope is significantly different from zero.

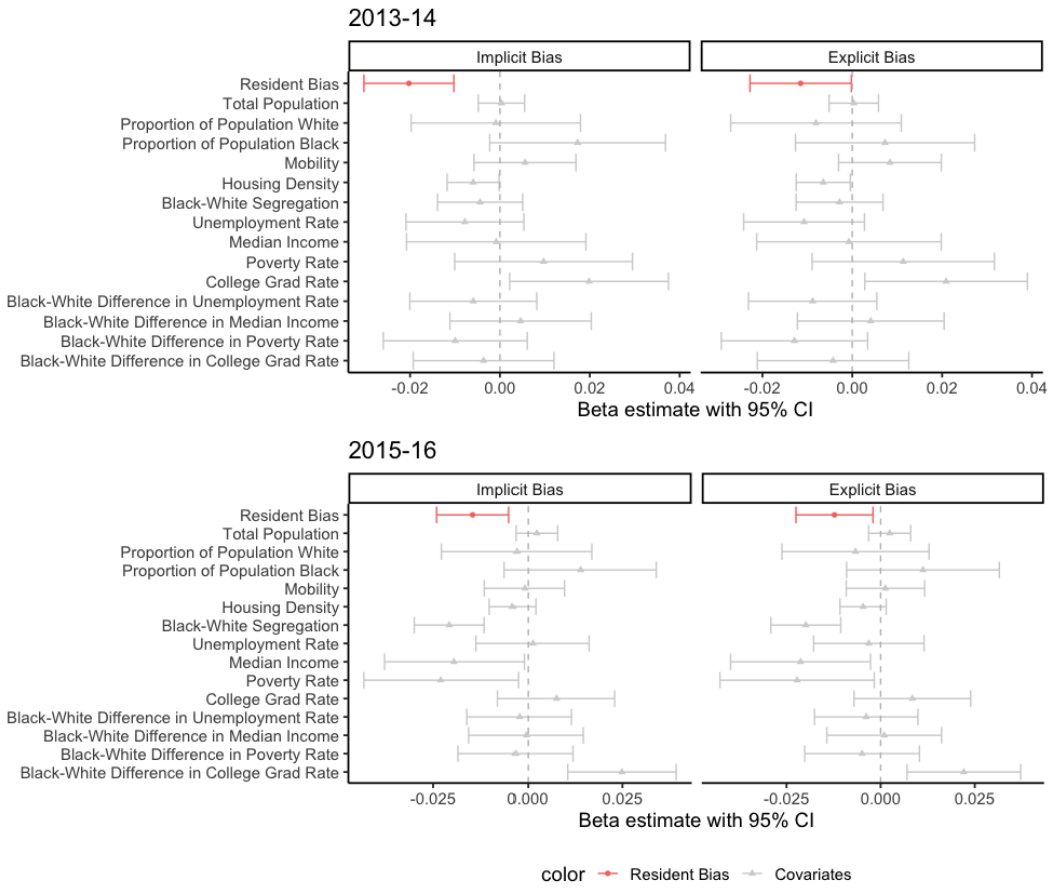
AP Exam Passing

As reported in the main text, residents' implicit and explicit bias consistently predicted *smaller* Black-White gaps in AP exam passing rates (Figure A11). When examining Black and White students separately, implicit and explicit bias did not predict exam taking rates for both groups (Figure A12-13), with the exception of implicit bias in 2013-14 predicting lower passing rates for White students).

A weaker but similar pattern emerged in the binomial regressions. Specifically, although point estimates of the key interaction (race and bias) were consistently negative—indicating *smaller* differences in the probability of passing AP exams in more biased counties—the estimates were not significantly different from zero, with the exception of explicit bias in 2015-16 ($p = 0.026$; Figure A14). Simple slopes suggest that bias is associated with a lower likelihood of passing AP exams for White students ($ps < 0.113$) but not of Black students ($ps > 0.162$; Figure A15).

Black-White Exam Passing Rate Gap

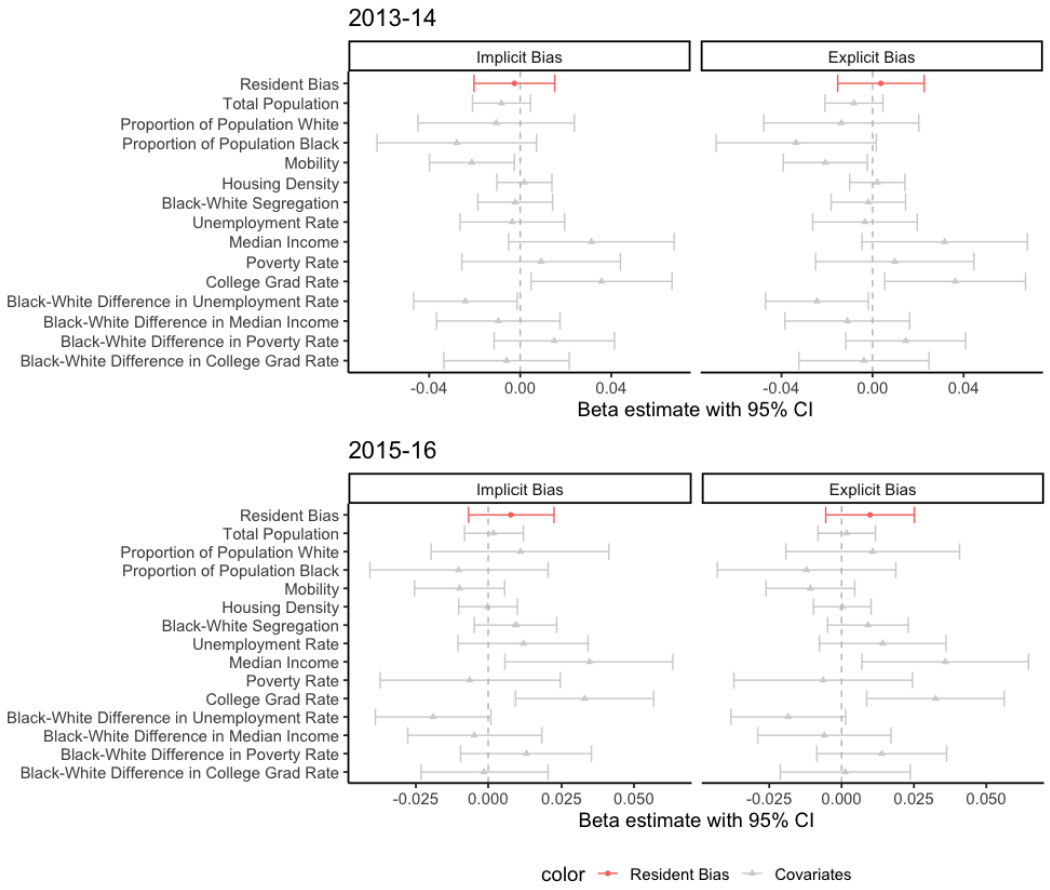
Figure A11. Coefficient estimates of key predictors (residents' implicit and explicit bias) and county-level covariates predicting Black-White gaps in AP exam passing rates.



Note. All variables were standardized prior to estimation for comparability. Bars represent 95% confidence intervals.

Black Exam Passing Rate

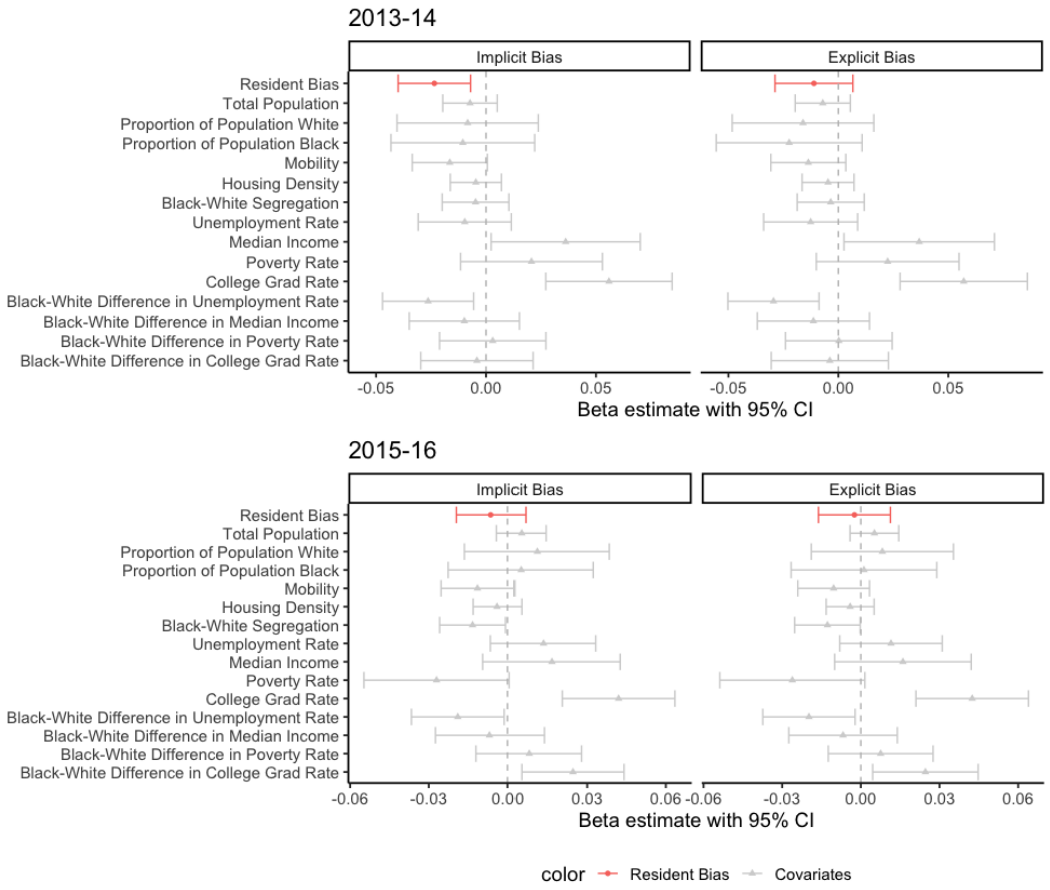
Figure A12. Coefficient estimates of key predictors (residents' implicit and explicit bias) and county-level covariates predicting AP exam passing rates for Black students.



Note. All variables were standardized prior to estimation for comparability. Bars represent 95% confidence intervals.

White Exam Passing Rate

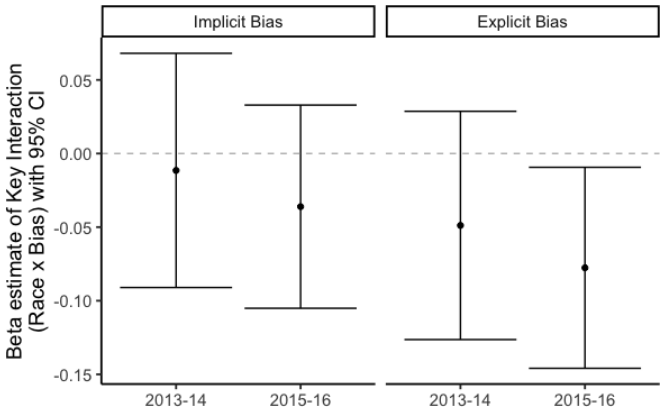
Figure A13. Coefficient estimates of key predictors (residents' implicit and explicit bias) and county-level covariates predicting AP exam passing rates for White students.



Note. All variables were standardized prior to estimation for comparability. Bars represent 95% confidence intervals.

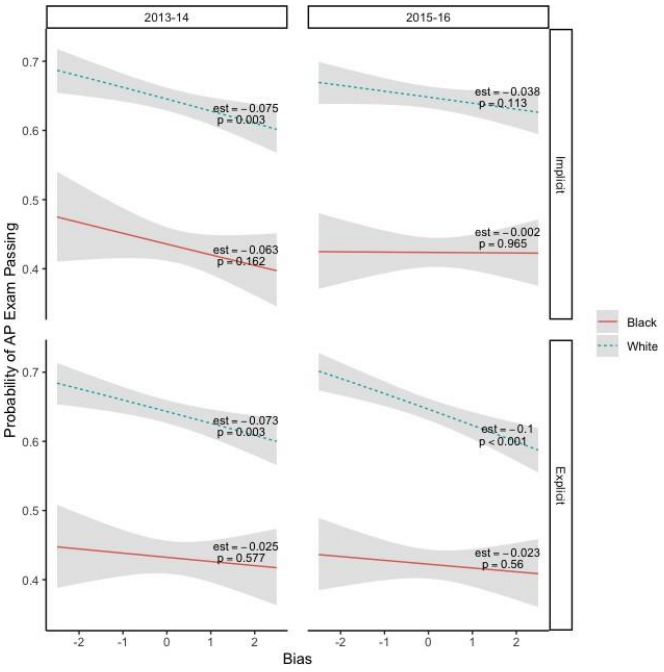
Robustness Check: Binomial Regression

Figure A14. Coefficient estimates of the key predictor (interaction between race and bias) predicting the probability of passing AP exam.



Note. Bars represent 95% confidence intervals.

Figure A15. Simple slopes of bias on the probability of AP exam passing for Black versus White students.



Note. Bands represent corresponding 95% confidence intervals; *est* represents the estimate of the simple slope; *p* represents p-value indicating whether the slope is significantly different from zero.

Mediation Analyses

AP Course Enrollment

Robustness Check #1: Using Counties with More Teacher Respondents

We repeated the mediation analyses using a progressively smaller set of counties that had at least 30, 50, or 100 White teachers who completed the Project Implicit Race IAT (compared to 10). These samples are more conservative in regard to sample size, but increase the reliability of teacher bias estimates. Across all years and samples, teachers' implicit bias continued to significantly mediate the relationship between residents' implicit bias and Black-White gaps in AP course enrollment rates. In contrast, teachers' explicit bias in 2015-16 and 2017-18 no longer significantly mediated the relationship between residents' explicit bias and enrollment gaps, perhaps implying that explicit bias plays a less influential role than implicit bias on teacher-student dynamics that shape students' enrollment outcomes.

Table A2a. Mediation results for implicit bias in 2013-14.

	10+ teachers (Preregistered)	30+ teachers	50+ teachers	100+ teachers
Structural				
a-path	-0.045 (0.020)*	-0.046 (0.021)*	-0.044 (0.022)*	-0.045 (0.026).
b-path	-0.013 (0.004)**	-0.016 (0.005)**	-0.016 (0.006)**	-0.022 (0.009)*
Indirect (a*b)	0.001 (0.000).	0.001 (0.000).	0.001 (0.000)	0.001 (0.001)
Developmental				
a-path	-0.093 (0.037)*	-0.071 (0.038).	-0.054 (0.041)	-0.044 (0.050)
b-path	0.018 (0.003)***	0.019 (0.004)***	0.015 (0.004)***	0.014 (0.005)**
Indirect (a*b)	-0.002 (0.001)*	-0.001 (0.001).	-0.001 (0.001)	-0.001 (0.001)
Interpersonal				
a-path	0.661 (0.046)***	0.639 (0.050)***	0.614 (0.055)***	0.618 (0.068)***
b-path	0.006 (0.002)*	0.006 (0.003)*	0.007 (0.003)*	0.009 (0.003)**
Indirect (a*b)	0.004 (0.002)*	0.004 (0.002)*	0.004 (0.002)*	0.005 (0.002)*
Direct (c')	-0.002 (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.005 (0.004)
Total (c)	0.001 (0.002)	0.001 (0.002)	0.001 (0.003)	0.000 (0.003)
N schools	6128	5455	4975	4065
N counties	580	414	322	194

Table A2b. Mediation results for explicit bias in 2013-14.

	10+ teachers (Preregistered)	30+ teachers	50+ teachers	100+ teachers
Structural				
a-path	-0.065 (0.022)**	-0.064 (0.024)**	-0.071 (0.025)**	-0.066 (0.026)*
b-path	-0.012 (0.004)**	-0.014 (0.005)**	-0.015 (0.006)*	-0.021 (0.009)*
Indirect (a*b)	0.001 (0.000)*	0.001 (0.000)*	0.001 (0.001).	0.001 (0.001).
Developmental				
a-path	-0.028 (0.040)	-0.009 (0.042)	0.000 (0.046)	0.017 (0.056)
b-path	0.018 (0.003)***	0.019 (0.004)***	0.016 (0.004)***	0.015 (0.004)**
Indirect (a*b)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Interpersonal				
a-path	0.776 (0.052)***	0.777 (0.055)***	0.797 (0.059)***	0.827 (0.075)***
b-path	0.006 (0.002)*	0.006 (0.003).	0.005 (0.003)	0.009 (0.004)*
Indirect (a*b)	0.004 (0.002)*	0.004 (0.002).	0.004 (0.003)	0.008 (0.003)*
Direct (c')	0.000 (0.003)	0.001 (0.004)	0.001 (0.004)	-0.003 (0.005)
Total (c)	0.005 (0.003)*	0.006 (0.003)*	0.006 (0.003).	0.006 (0.004).
N schools	6128	5455	4975	4065
N counties	580	414	322	194

Note. Schools were included if there were at least 10 Black and 10 White students enrolled in grades 9-12. Counties were included if data on all three mediators were available. The first column corresponds to the preregistered sample, in which teacher bias estimates were calculated for counties with at least 10 White teachers who completed the Project Implicit Race IAT. The following columns correspond to a progressively smaller set of samples, in which teacher bias estimates were calculated for counties with at least 30, 50, or 100 White teachers who completed the Project Implicit Race IAT.

Table A3a. Mediation results for implicit bias in 2015-16.

	10+ teachers (Preregistered)	30+ teachers	50+ teachers	100+ teachers
Structural				
a-path	-0.042 (0.019)*	-0.041 (0.020)*	-0.036 (0.021).	-0.033 (0.023)
b-path	-0.007 (0.004).	-0.007 (0.005)	-0.008 (0.006)	-0.005 (0.008)
Indirect (a*b)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Developmental				
a-path	-0.103 (0.038)**	-0.099 (0.041)*	-0.081 (0.043).	-0.072 (0.049)
b-path	0.025 (0.003)***	0.025 (0.003)***	0.026 (0.004)***	0.026 (0.005)***
Indirect (a*b)	-0.003 (0.001)*	-0.002 (0.001)*	-0.002 (0.001).	-0.002 (0.001)
Interpersonal				
a-path	0.683 (0.045)***	0.671 (0.047)***	0.651 (0.051)***	0.642 (0.058)***
b-path	0.011 (0.003)***	0.011 (0.003)***	0.011 (0.003)***	0.013 (0.004)***
Indirect (a*b)	0.007 (0.002)***	0.007 (0.002)***	0.007 (0.002)***	0.009 (0.003)***
Direct (c')	0.000 (0.003)	0.000 (0.003)	0.001 (0.003)	0.001 (0.004)
Total (c)	0.005 (0.002)*	0.005 (0.002)*	0.006 (0.003)*	0.008 (0.003)*
N schools	6788	6178	5612	4751
N counties	615	467	362	237

Table A3b. Mediation results for explicit bias in 2015-16.

	10+ teachers (Preregistered)	30+ teachers	50+ teachers	100+ teachers
Structural				
a-path	-0.071 (0.019)***	-0.073 (0.020)***	-0.062 (0.021)**	-0.058 (0.023)*
b-path	-0.006 (0.004).	-0.006 (0.005)	-0.006 (0.006)	-0.003 (0.008)
Indirect (a*b)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Developmental				
a-path	-0.075 (0.043).	-0.057 (0.046)	-0.042 (0.049)	-0.035 (0.057)
b-path	0.025 (0.003)***	0.025 (0.003)***	0.027 (0.004)***	0.028 (0.005)***
Indirect (a*b)	-0.002 (0.001).	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.002)
Interpersonal				
a-path	0.735 (0.047)***	0.741 (0.049)***	0.757 (0.053)***	0.774 (0.065)***
b-path	0.006 (0.002)*	0.004 (0.003)	0.004 (0.003)	0.004 (0.004)
Indirect (a*b)	0.004 (0.002)*	0.003 (0.002)	0.003 (0.002)	0.003 (0.003)
Direct (c')	0.002 (0.003)	0.003 (0.003)	0.005 (0.004)	0.006 (0.005)
Total (c)	0.004 (0.002).	0.006 (0.003)*	0.007 (0.003)*	0.009 (0.003)*
N schools	6788	6178	5612	4751
N counties	615	467	362	237

Note. Schools were included if there were at least 10 Black and 10 White students enrolled in grades 9-12. Counties were included if data on all three mediators were available. The first column corresponds to the preregistered sample, in which teacher bias estimates were calculated for counties with at least 10 White teachers who completed the Project Implicit Race IAT. The following columns correspond to a progressively smaller set of samples, in which teacher bias estimates were calculated for counties with at least 30, 50, or 100 White teachers who completed the Project Implicit Race IAT.

Table A4a. Mediation results for implicit bias in 2017-18.

	10+ teachers (Preregistered)	30+ teachers	50+ teachers	100+ teachers
Structural				
a-path	-0.022 (0.017)	-0.022 (0.018)	-0.022 (0.018)	-0.019 (0.019)
b-path	-0.006 (0.004)	-0.007 (0.004).	-0.010 (0.005)*	-0.012 (0.006)*
Indirect (a*b)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Developmental				
a-path	-0.096 (0.039)*	-0.090 (0.041)*	-0.075 (0.042).	-0.044 (0.046)
b-path	0.022 (0.003)***	0.022 (0.003)***	0.023 (0.003)***	0.021 (0.004)***
Indirect (a*b)	-0.002 (0.001)*	-0.002 (0.001)*	-0.002 (0.001).	-0.001 (0.001)
Interpersonal				
a-path	0.751 (0.041)***	0.746 (0.043)***	0.741 (0.044)***	0.742 (0.050)***
b-path	0.010 (0.002)***	0.009 (0.002)***	0.010 (0.003)***	0.012 (0.003)***
Indirect (a*b)	0.007 (0.002)***	0.007 (0.002)***	0.008 (0.002)***	0.009 (0.002)***
Direct (c')				
Total (c)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.002 (0.003)
N schools	0.006 (0.002)**	0.007 (0.002)**	0.008 (0.003)**	0.010 (0.003)***
N counties	6885	6483	6101	5391

Table A4b. Mediation results for explicit bias in 2017-18.

	10+ teachers (Preregistered)	30+ teachers	50+ teachers	100+ teachers
Structural				
a-path	-0.073 (0.019)***	-0.070 (0.019)***	-0.069 (0.020)***	-0.055 (0.021)**
b-path	-0.005 (0.004)	-0.006 (0.004)	-0.008 (0.005)	-0.009 (0.006)
Indirect (a*b)	0.000 (0.000)	0.000 (0.000)	0.001 (0.000)	0.000 (0.000)
Developmental				
a-path	-0.093 (0.043)*	-0.076 (0.045).	-0.061 (0.046)	-0.021 (0.051)
b-path	0.022 (0.003)***	0.022 (0.003)***	0.023 (0.003)***	0.021 (0.004)***
Indirect (a*b)	-0.002 (0.001)*	-0.002 (0.001).	-0.001 (0.001)	0.000 (0.001)
Interpersonal				
a-path	0.809 (0.039)***	0.816 (0.040)***	0.823 (0.041)***	0.862 (0.047)***
b-path	0.006 (0.003)*	0.005 (0.003).	0.005 (0.003)	0.004 (0.004)
Indirect (a*b)	0.005 (0.002)*	0.004 (0.002).	0.004 (0.003)	0.003 (0.003)
Direct (c')				
Total (c)	0.002 (0.003)	0.004 (0.003)	0.004 (0.004)	0.007 (0.004)
N schools	0.005 (0.003)*	0.006 (0.003)*	0.007 (0.003)*	0.010 (0.003)**
N counties	6885	6483	6101	5391

Note. Schools were included if there were at least 10 Black and 10 White students enrolled in grades 9-12. Counties were included if data on all three mediators were available. The first column corresponds to the preregistered sample, in which teacher bias estimates were calculated for counties with at least 10 White teachers who completed the Project Implicit Race IAT. The following columns correspond to a progressively smaller set of samples, in which teacher bias estimates were calculated for counties with at least 30, 50, or 100 White teachers who completed the Project Implicit Race IAT.

Robustness Check #2: Using Teacher Sexuality Bias as the Interpersonal Mediator

To determine whether teachers' *racial* bias uniquely explains the relationship between residents' racial bias and AP course enrollment gaps, we repeated the mediation analyses using teachers' *sexuality* bias as an interpersonal mediator. While residents' racial bias was positively and significantly associated with teachers' sexuality bias (a-path), teachers' sexuality bias was not associated with AP course enrollment gaps (b-path), yielding non-significant indirect effects across all years and both types of bias.

Table A5a. Mediation results, replacing teacher racial implicit bias with sexuality implicit bias.

	2013-14	2015-16	2017-18
Structural			
a-path	-0.051 (0.022)*	-0.042 (0.020)*	-0.018 (0.017)
b-path	-0.015 (0.005)**	-0.006 (0.005)	-0.006 (0.004)
Indirect (a*b)	0.001 (0.000).	0.000 (0.000)	0.000 (0.000)
Developmental			
a-path	-0.076 (0.038)*	-0.102 (0.040)*	-0.085 (0.040)*
b-path	0.018 (0.004)***	0.026 (0.003)***	0.023 (0.003)***
Indirect (a*b)	-0.001 (0.001).	-0.003 (0.001)*	-0.002 (0.001)*
Interpersonal			
a-path	0.411 (0.062)***	0.411 (0.049)***	0.446 (0.050)***
b-path	0.003 (0.002)	0.001 (0.002)	0.002 (0.002)
Indirect (a*b)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Direct (c')	0.001 (0.003)	0.006 (0.003)*	0.007 (0.002)**
Total (c)	0.001 (0.002)	0.004 (0.002).	0.006 (0.002)**
N schools	5466	6311	6527
N counties	420	502	529

Table A5b. Mediation results, replacing teacher racial explicit bias with sexuality explicit bias.

	2013-14	2015-16	2017-18
Structural			
a-path	-0.070 (0.024)**	-0.071 (0.020)***	-0.073 (0.019)***
b-path	-0.014 (0.005)**	-0.006 (0.005)	-0.005 (0.004)
Indirect (a*b)	0.001 (0.000)*	0.000 (0.000)	0.000 (0.000)
Developmental			
a-path	-0.007 (0.042)	-0.067 (0.045)	-0.077 (0.044).
b-path	0.018 (0.004)***	0.026 (0.003)***	0.022 (0.003)***
Indirect (a*b)	0.000 (0.001)	-0.002 (0.001)	-0.002 (0.001).
Interpersonal			
a-path	0.493 (0.062)***	0.475 (0.050)***	0.513 (0.045)***
b-path	-0.001 (0.002)	0.002 (0.002)	0.000 (0.002)
Indirect (a*b)	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)
Direct (c')	0.006 (0.003).	0.006 (0.003)*	0.007 (0.003)**
Total (c)	0.006 (0.003)*	0.005 (0.003)*	0.006 (0.003)*
N schools	5466	6311	6527
N counties	420	502	529

Note. Schools were included if there were at least 10 Black and 10 White students enrolled in grades 9-12. Counties were included if data on all three mediators were available. Interpersonal mediator (teacher sexuality bias) was calculated only for counties in which at least 10 White teachers completed the Project Implicit Sexuality IAT.

AP Exam Taking

On an exploratory basis, we examined whether any of our proposed mediators—structural (concentration of AP courses in predominantly White schools), developmental (Black-White prior achievement gaps), or interpersonal (teacher racial bias)—explain the associations between residents' racial bias and AP exam taking gaps. None of these features emerged as a significant mediator across years. Most notably, while resident bias continued to be significantly and positively associated with teacher bias, teacher bias was no longer linked to AP exam taking gaps—supporting the idea that bias primarily manifests during the selection process, rather than influencing outcomes once students are enrolled.

Table A6a. Mediation results modeling Black-White gaps in AP exam taking, implicit bias.

	2013-14	2015-16	2017-18
Structural			
a-path	-0.061 (0.024)*	-0.034 (0.021)	-0.038 (0.020).
b-path	-0.003 (0.009)	-0.010 (0.009)	-0.008 (0.008)
Indirect (a*b)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)
Developmental			
a-path	-0.069 (0.042)	-0.083 (0.043).	-0.088 (0.043)*
b-path	0.025 (0.008)**	0.003 (0.007)	0.008 (0.007)
Indirect (a*b)	-0.002 (0.001)	0.000 (0.001)	-0.001 (0.001)
Interpersonal			
a-path	0.649 (0.055)***	0.679 (0.049)***	0.743 (0.043)***
b-path	0.007 (0.006)	0.002 (0.005)	0.005 (0.005)
Indirect (a*b)	0.005 (0.004)	0.001 (0.003)	0.004 (0.004)
Direct (c')	-0.019 (0.006)**	-0.022 (0.006)***	-0.014 (0.005)**
Total (c)	-0.016 (0.005)**	-0.020 (0.004)***	-0.011 (0.004)*
N schools	2864	3451	3393
N counties	468	513	511

Table A6b. Mediation results modeling Black-White gaps in AP exam taking, explicit bias.

	2013-14	2015-16	2017-18
Structural			
a-path	-0.090 (0.026)***	-0.068 (0.022)**	-0.087 (0.021)***
b-path	-0.001 (0.010)	-0.008 (0.009)	-0.006 (0.008)
Indirect (a*b)	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)
Developmental			
a-path	-0.043 (0.045)	-0.080 (0.046).	-0.110 (0.046)*
b-path	0.026 (0.008)***	0.005 (0.007)	0.010 (0.007)
Indirect (a*b)	-0.001 (0.001)	0.000 (0.001)	-0.001 (0.001)
Interpersonal			
a-path	0.748 (0.060)***	0.702 (0.054)***	0.791 (0.043)***
b-path	0.005 (0.006)	0.004 (0.005)	0.002 (0.005)
Indirect (a*b)	0.004 (0.004)	0.003 (0.003)	0.002 (0.004)
Direct (c')	-0.007 (0.008)	-0.009 (0.005).	0.000 (0.006)
Total (c)	-0.004 (0.006)	-0.006 (0.004)	0.001 (0.004)
N schools	2864	3451	3393
N counties	468	513	511

Note. Schools were included if there were at least 10 Black and 10 White students enrolled in at least one AP course. Counties were included if data on all three mediators were available. Interpersonal mediator (teacher racial bias) was calculated only for counties in which at least 10 White teachers completed the Project Implicit Race IAT.

AP Exam Passing

On an exploratory basis, we examined whether any of our proposed mediators—structural (concentration of AP courses in predominantly White schools), developmental (Black-White prior achievement gaps), or interpersonal (teacher racial bias)—explain the associations between residents' racial bias and AP exam passing gaps. Similar to exam taking, none of these features emerged as a significant mediator across all years.

Table A7a. Mediation results modeling Black-White gaps in AP exam passing, implicit bias.

	2013-14	2015-16
Structural		
a-path	-0.033 (0.029)	-0.003 (0.024)
b-path	-0.025 (0.012)*	-0.021 (0.010)*
Indirect (a*b)	0.001 (0.001)	0.000 (0.001)
Developmental		
a-path	-0.069 (0.050)	-0.075 (0.047)
b-path	0.025 (0.008)**	0.034 (0.007)***
Indirect (a*b)	-0.002 (0.001)	-0.003 (0.002)
Interpersonal		
a-path	0.667 (0.059)***	0.679 (0.052)***
b-path	-0.004 (0.005)	-0.005 (0.006)
Indirect (a*b)	-0.003 (0.003)	-0.004 (0.004)
Direct (c')	-0.018 (0.006)**	-0.010 (0.008)
Total (c)	-0.021 (0.006)***	-0.016 (0.006)**
N schools	1568	2066
N counties	335	406

Table A7b. Mediation results modeling Black-White gaps in AP exam passing, explicit bias.

	2013-14	2015-16
Structural		
a-path	-0.055 (0.030).	-0.033 (0.026)
b-path	-0.025 (0.012)*	-0.023 (0.010)*
Indirect (a*b)	0.001 (0.001)	0.001 (0.001)
Developmental		
a-path	-0.040 (0.054)	-0.071 (0.055)
b-path	0.026 (0.008)**	0.035 (0.007)***
Indirect (a*b)	-0.001 (0.001)	-0.002 (0.002)
Interpersonal		
a-path	0.722 (0.066)***	0.657 (0.059)***
b-path	0.003 (0.006)	-0.007 (0.005)
Indirect (a*b)	0.002 (0.004)	-0.005 (0.004)
Direct (c')	-0.018 (0.007)*	-0.006 (0.006)
Total (c)	-0.015 (0.006)*	-0.013 (0.005)*
N schools	1568	2066
N counties	335	406

Note. Schools were included if there were at least 10 Black and 10 White students who have taken at least one AP exam. Counties were included if data on all three mediators were available. Interpersonal mediator (teacher racial bias) was calculated only for counties in which at least 10 White teachers completed the Project Implicit Race IAT.

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Non-Preregistered Outcomes

Across all studies, expected performance was computed as the average of expected performance in AP English class and AP English exam (on a scale of 1 to 10). Overall, the results were similar but weaker than the analyses using priority tier decision as an outcome. For implicit bias, the key interaction between race and bias was not significant ($p = 0.179$), but implicit bias significantly predicted lower expectations of Black students only ($p = 0.012$), and not of White students ($p = 0.133$). For explicit bias, the key interaction was marginally significant ($p = 0.081$), explained by explicit bias marginally associated with lower expectations of Black students ($p = 0.099$) but not of White students ($p = 0.748$).

Table B1a. Regression coefficients of implicit bias, race, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Pilot Study).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	7.226	0.114	<0.001	7.000	7.452
Race	-0.372	0.096	<0.001	-0.559	-0.184
Bias	-0.447	0.203	0.029	-0.849	-0.045
Race x Bias	**0.229**	**0.170**	**0.179**	**-0.105**	**0.563**
Slope of Bias for Black Students	-0.562	0.220	0.012	-0.996	-0.127
Slope of Bias for White Students	-0.333	0.220	0.133	-0.767	0.102

Table B1b. Regression coefficients of explicit bias, race, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Pilot Study).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	7.036	0.100	<0.001	6.838	7.235
Race	-0.241	0.083	0.004	-0.404	-0.078
Bias	-0.053	0.049	0.286	-0.150	0.045
Race x Bias	**0.071**	**0.041**	**0.081**	**-0.009**	**0.151**
Slope of Bias for Black Students	-0.088	0.053	0.099	-0.193	0.017
Slope of Bias for White Students	-0.017	0.053	0.748	-0.122	0.088

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as its interaction with race and bias, was included in the regression but not shown for parsimony. Bolded coefficients highlight the key interaction effect, indicating whether bias differently predicts evaluations of Black versus White students.

STUDY 1

Non-Preregistered Outcomes

Results for implicit bias were generally similar to the analyses using preregistered outcomes. Greater implicit bias was associated with significantly lower expectations of Black students ($p = 0.025$) but not of White students ($p = 0.173$), but the interaction term formally assessing the Black and White slopes was not significant ($p = 0.208$). Results for explicit bias were similar to the analyses using binary decision as an outcome. Specifically, explicit bias was not associated with expectations of either Black ($p = 0.826$) or White students ($p = 0.720$), yielding a null interaction ($p = 0.403$).

Table B2a. Regression coefficients of implicit bias, race, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Study 1).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	7.510	0.094	<0.001	7.324	7.695
Race	-0.097	0.070	0.165	-0.235	0.040
Bias	-0.326	0.169	0.055	-0.658	0.007
Race x Bias	**0.158**	**0.125**	**0.208**	**-0.088**	**0.403**
Slope of Bias for Black Students	-0.404	0.179	0.025	-0.758	-0.051
Slope of Bias for White Students	-0.247	0.181	0.173	-0.603	0.109

Table B2b. Regression coefficients of explicit bias, race, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Study 1).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	7.396	0.075	<0.001	7.249	7.543
Race	-0.046	0.055	0.407	-0.154	0.063
Bias	-0.004	0.055	0.941	-0.113	0.105
Race x Bias	**-0.034**	**0.041**	**0.403**	**-0.114**	**0.046**
Slope of Bias for Black Students	0.013	0.059	0.826	-0.103	0.129
Slope of Bias for White Students	-0.021	0.059	0.720	-0.138	0.095

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as its interaction with race and bias, was included in the regression but not shown for parsimony. Bolded coefficients highlight the key interaction effect, indicating whether bias differently predicts evaluations of Black versus White students.

STUDY 2

Non-Preregistered Outcomes

Results for implicit bias were similar to the analyses using preregistered outcomes. Implicit bias was not significantly associated with expectations of either Black ($p = 0.120$) or White students ($p = 0.056$), yielding a null interaction ($p = 0.578$). For explicit bias, the pattern for simple slopes differed from the analyses using preregistered outcomes (where slopes were not significant), but the overall implication remained the same. Specifically, explicit bias predicted significantly lower expectations of Black students ($p = 0.026$) and marginally lower expectations of White students ($p = 0.063$) but to a comparable extent, yielding a null interaction ($p = 0.696$).

Table B3a. Regression coefficients of implicit bias, race, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Study 2).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	7.256	0.109	<0.001	7.041	7.472
Race	-0.009	0.088	0.915	-0.182	0.163
Bias	-0.381	0.204	0.062	-0.782	0.019
Race x Bias	**-0.091**	**0.163**	**0.578**	**-0.411**	**0.230**
Slope of Bias for Black Students	-0.336	0.216	0.120	-0.760	0.088
Slope of Bias for White Students	-0.427	0.223	0.056	-0.865	0.012

Table B3b. Regression coefficients of explicit bias, race, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Study 2).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	7.113	0.080	<0.001	6.955	7.271
Race	-0.042	0.064	0.515	-0.169	0.085
Bias	-0.092	0.042	0.028	-0.175	-0.010
Race x Bias	**0.013**	**0.034**	**0.696**	**-0.053**	**0.079**
Slope of Bias for Black Students	-0.099	0.044	0.026	-0.186	-0.012
Slope of Bias for White Students	-0.086	0.046	0.063	-0.176	0.005

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as its interaction with race and bias, was included in the regression but not shown for parsimony. Bolded coefficients highlight the key interaction effect, indicating whether bias differently predicts evaluations of Black versus White students.

PILOT STUDY FOR COGNITIVE LOAD

Methods

Participants

Participants were recruited from Cloud Research's research panels. Among 197 participants invited, 59 participants were not eligible to participate, either because they were not public high school teachers or did not identify as White. Among the remaining 138 participants, two participants indicated that they answered randomly at some point throughout the study, 19 additional participants exhibited careless responding patterns on the IAT, and 19 additional participants failed the attention check (i.e., did not recall seeing race or name information on students' applications), leaving 98 participants included in the final sample (M_{age} = 42.7, SD_{age} = 13.0; $M_{years\ of\ teaching}$ = 12.9, $SD_{years\ of\ teaching}$ = 8.8; 49.0% men, 51.0% women). The rate of failing attention check did not differ by conditions ($\chi^2(1, 117) = 1.09$, $p = 0.297$).

Procedures

Participants were told that the purpose of the research is to understand how people make decisions while multi-tasking, and as such, they would be asked to do two things at once: evaluating students and remembering a string of letters. They were instructed to try their best to memorize it without relying on shortcuts (such as writing it down), and that they would be asked to recall the string once they complete the evaluation task. Participants were then presented with either a 8-letter string ("NWRBRKPJ") or a 2-letter string ("KL"), depending on the condition they were assigned to. The length of the string for the high cognitive load condition was determined based on the classic finding that an average person can hold approximately seven discrete items in their short-term memory (Miller, 1956). Participants were required to stay on the page for 10 seconds, but they could stay however longer they wanted to memorize the string.

Participants then reviewed the same application materials (used in previous studies) and made placement decisions. Subsequently, they completed the same attention check as in Studies 1-2, followed by a string recall question, a cognitive load manipulation check, compliance checks, implicit and explicit bias measures (with order counterbalanced), and demographic questions.

Measures

All student evaluation and racial bias measures were identical to previous studies.

Cognitive Load Manipulation Check

Participants rated their agreement with the following statement on a 1 (*Totally disagree*) to 5 (*Totally agree*) Likert scale: "While reviewing students' application, I was mainly thinking of the string I had to remember."

Compliance Checks

Participants answered four questions assessing their compliance with our instruction: whether they evaluated students randomly (e.g., provided similar ratings across students without reviewing the individual applications), used any shortcuts to recall the letter string (e.g., writing it down), tried to remember the letter string at all, or gave up trying to remember it at some point.

Results

Although the pilot study was underpowered, we conducted exploratory analyses to examine whether the relationship between bias and priority tier placement decisions for Black versus White students differed across the two conditions. The analytic model mirrored those used in previous studies, with the addition of experimental condition as a predictor (analogous to the model used in Chapter 3, Studies 2-3). We focused on the two-way interaction between race and bias (implicit or explicit) within each load condition (high or low).

For implicit bias, the interaction between race and bias was not significant in both low (b = 0.137, SE = 0.177, p = 0.440, 95% CI [-0.211, 0.485]) and high cognitive load (b = -0.184, SE = 0.221, p = 0.405, 95% CI [-0.619, 0.250]) condition. In the low load condition, implicit bias was not associated with priority tier decisions for either Black (b = -0.222, SE = 0.195, p = 0.258, 95% CI [-0.608, 0.164]) or White students (b = -0.085, SE = 0.195, p = 0.663, 95% CI [-0.471, 0.301]). Similarly, in the high load condition, implicit bias was not associated with priority tier decisions for either Black (b = -0.204, SE = 0.244, p = 0.404, 95% CI [-0.686, 0.278]) or White students (b = -0.388, SE = 0.244, p = 0.114, 95% CI [-0.870, 0.094]).

Results for explicit bias were largely the same. The interaction between race and bias was not significant in both low (b = 0.007, SE = 0.028, p = 0.809, 95% CI [-0.048, 0.062]) and high cognitive load (b = 0.045, SE = 0.034, p = 0.179, 95% CI [-0.021, 0.111]) condition. In the low load condition, explicit bias was not associated with priority tier decisions for either Black (b = 0.034, SE = 0.031, p = 0.268, 95% CI [-0.027, 0.096]) or White students (b = 0.041, SE = 0.031, p = 0.185, 95% CI [-0.020, 0.103]). Similarly, in the high load condition, explicit bias was not associated with priority tier decisions for either Black (b = -0.019, SE = 0.037, p = 0.608, 95% CI [-0.092, 0.054]) or White students (b = 0.026, SE = 0.037, p = 0.483, 95% CI [-0.047, 0.099]).

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STUDY 1

Explicit Bias

Priority Tier Decision

The main effect for explicit bias was significant (b = -0.047, SE = 0.014, p = 0.001, 95% CI [-0.075, -0.019]), such that more explicitly biased individuals generally placed students more stringently. The main effect of race was also significant (b = -0.136, SE = 0.031, p < 0.001, 95% CI [-0.197, -0.074]) such that participants placed White students into lower tiers than Black students. These main effects, again, were qualified by the hypothesized interaction (b = 0.055, SE = 0.016, p = 0.001, 95% CI [0.023, 0.087]), driven by more explicitly biased individuals placing Black students into lower priority tiers (b = -0.074, SE = 0.017, p < 0.001, 95% CI [-0.108, -0.040]) rather than White students (b = -0.019, SE = 0.016, p = 0.217, 95% CI [-0.050, 0.011]).

Binary Decision

The main effect of explicit bias was not significant (b = -0.547, SE = 0.390, p = 0.161, 95% CI [-1.311, 0.217]) but the main effect of student race was (b = -5.847, SE = 1.254, p < 0.001, 95% CI [-8.305, -3.390]). Again, this main effect was qualified by the hypothesized interaction between race and explicit bias (b = 1.884, SE = 0.688, p = 0.006, 95% CI [0.535, 3.232]), driven by more explicitly biased individuals being less likely to admit Black students (b = -1.489, SE = 0.704, p = 0.034, 95% CI [-2.868, -0.110]) and marginally more likely to admit White students (b = 0.395, SE = 0.214, p = 0.065, 95% CI [-0.024, 0.813]).

Non-Preregistered Outcomes

Across all studies, expected performance was computed as the average of expected performance in AP English class and AP English exam (on a scale of 1 to 10). Overall, the results were similar to the analyses using preregistered outcomes: The key term of interest (race x implicit bias) was significant. Similar to the binary placement decision, this interaction was driven by implicit bias predicting significantly higher expectations about White students, rather than lower expectations about Black students. The interaction between race and explicit bias was also significant, primarily driven by explicit bias predicting significantly lower expectations about Black students.

Table C1a. Regression coefficients of implicit bias, race, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Study 1).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	7.004	0.107	<0.001	6.794	7.214
Race	-0.525	0.092	<0.001	-0.706	-0.344
Bias	0.056	0.183	0.760	-0.304	0.416
Race x Bias	**0.737**	**0.158**	**<0.001**	**0.426**	**1.047**
Slope of Bias for Black Students	-0.313	0.201	0.121	-0.708	0.083
Slope of Bias for White Students	0.424	0.197	0.032	0.036	0.812

Table C1b. Regression coefficients of explicit bias, race, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Study 1).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	7.028	0.068	<0.001	6.893	7.162
Race	-0.198	0.061	0.001	-0.317	-0.079
Bias	-0.091	0.035	0.011	-0.161	-0.021
Race x Bias	**0.121**	**0.031**	**<0.001**	**0.060**	**0.183**
Slope of Bias for Black Students	-0.152	0.038	<0.001	-0.227	-0.076
Slope of Bias for White Students	-0.030	0.039	0.437	-0.107	0.046

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as its interaction with race and bias, was included in the regression but not shown for parsimony. Bolded coefficients highlight the key interaction effect, indicating whether bias differently predicts evaluations of Black versus White students.

Analyzing Data as Between-Subject

It is possible that social desirability concerns led participants to adjust their ratings over time (e.g., rating later applications more favorably than earlier applications) as they reviewed multiple applications. As described in the main text, all applications—except the one featuring a highly qualified student, which was always presented first to calibrate expectations—were presented in a random order. Therefore, any social desirability effects should not systematically influence ratings of specific applications. Nevertheless, to address this concern, we re-ran the analyses using only the second application (i.e., application that appeared right after the highly qualified student), treating the data as a between-subjects experiment. Only participants whose second application featured a Black or White student were included, resulting in a smaller sample ($N = 198$) than in the main within-subjects analyses. In this analysis, the interaction between implicit bias and student race was no longer significant for either of the preregistered outcomes ($ps < 0.620$). However, the simple slope of implicit bias for Black students was negative and trending ($ps < 0.126$), while the slope for White students was not significant ($ps > 0.409$).

Table C2a. Regression coefficients of implicit bias, race, and their interaction predicting priority tier decision, followed by simple slopes of bias for each race at average level of qualification, treating data as between-subject (Study 1).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	1.610	0.071	<0.001	1.471	1.750
Race	-0.143	0.142	0.313	-0.422	0.136
Bias	-0.214	0.123	0.083	-0.456	0.028
Race x Bias	**0.122**	**0.245**	**0.620**	**-0.362**	**0.606**
Slope of Bias for Black Students	-0.275	0.162	0.091	-0.593	0.044
Slope of Bias for White Students	-0.153	0.185	0.409	-0.517	0.211

Table C2b. Regression coefficients of explicit bias, race, and their interaction predicting priority tier decision, followed by simple slopes of bias for each race at average level of qualification, treating data as between-subject (Study 1).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	1.526	0.044	<0.001	1.440	1.612
Race	-0.072	0.087	0.410	-0.244	0.100
Bias	-0.085	0.025	0.001	-0.133	-0.036
Race x Bias	**-0.033**	**0.049**	**0.498**	**-0.131**	**0.064**
Slope of Bias for Black Students	-0.068	0.037	0.072	-0.142	0.006
Slope of Bias for White Students	-0.101	0.032	0.002	-0.165	-0.038

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as its interaction with race and bias, was included in the regression but not shown for parsimony. Bolded coefficients highlight the key interaction effect, indicating whether bias differently predicts evaluations of Black versus White students.

Table C3a. Regression coefficients of implicit bias, race, and their interaction predicting binary decision, followed by simple slopes of bias for each race at average level of qualification, treating data as between-subject (Study 1).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	1.740	0.338	<0.001	1.127	2.468
Race	-0.626	0.676	0.354	-1.994	0.730
Bias	-0.874	0.572	0.126	-2.047	0.209
Race x Bias	**-2.060**	**2.287**	**0.368**	**-6.574**	**2.476**
Slope of Bias for Black Students	-1.262	0.824	0.126	-2.877	0.353
Slope of Bias for White Students	-0.486	0.792	0.539	-2.039	1.067

Table C3b. Regression coefficients of explicit bias, race, and their interaction predicting binary decision, followed by simple slopes of bias for each race at average level of qualification, treating data as between-subject (Study 1).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	1.359	0.209	<0.001	0.972	1.802
Race	-0.129	0.419	0.757	-0.984	0.690
Bias	-0.292	0.150	0.052	-0.601	-0.008
Race x Bias	**0.661**	**0.599**	**0.270**	**-0.501**	**1.881**
Slope of Bias for Black Students	-0.207	0.187	0.266	-0.573	0.158
Slope of Bias for White Students	-0.376	0.234	0.109	-0.835	0.084

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as its interaction with race and bias, was included in the regression but not shown for parsimony. Bolded coefficients highlight the key interaction effect, indicating whether bias differently predicts evaluations of Black versus White students.

STUDY 2

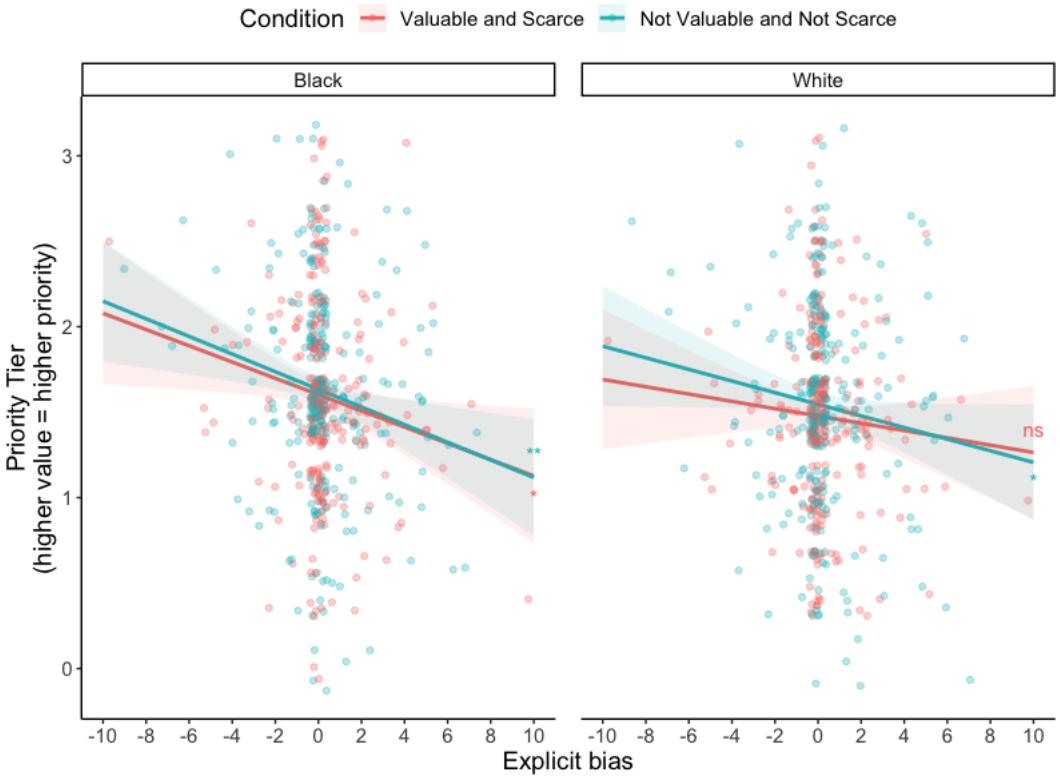
Explicit Bias

Priority Tier Decision

The main effects of explicit bias (b = -0.039, SE = 0.012, p = 0.001, 95% CI [-0.062, -0.015]) and student race (b = -0.106, SE = 0.022, p < 0.001, 95% CI [-0.149, -0.063]) were significant. Similar to Study 1, these main effects were qualified by a marginal interaction between explicit bias and race (b = 0.022, SE = 0.012, p = 0.062, 95% CI [-0.001, 0.045]), such that even though more explicitly biased participants generally placed students more stringently, they did so more strongly for Black students (b = -0.050, SE = 0.013, p < 0.001, 95% CI [-0.076, -0.023]) than for White students (b = -0.028, SE = 0.013, p = 0.037, 95% CI [-0.054, -0.002]).

In contrast to implicit bias, however, this pattern was not primarily driven by one condition or the other. The three-way interaction of explicit bias, race, and condition was negligible (b = 0.009, SE = 0.023, p = 0.713, 95% CI [-0.037, 0.055]), with the two-way interaction of explicit bias and race comparable in size across conditions (*Valuable and Scarce*: b = 0.026, SE = 0.018, p = 0.141, 95% CI [-0.009, 0.061]; *Not Valuable and Not Scarce*: b = 0.018, SE = 0.015, p = 0.249, 95% CI [-0.012, 0.048]). In both conditions, greater explicit bias predicted placement of Black students into lower priority tiers (*Valuable and Scarce*: b = -0.048, SE = 0.020, p = 0.019, 95% CI [-0.087, -0.008]; *Not Valuable and Not Scarce*: b = -0.052, SE = 0.017, p = 0.003, 95% CI [-0.086, -0.018]) more reliably than of White students (*Valuable and Scarce*: b = -0.021, SE = 0.020, p = 0.288, 95% CI [-0.061, 0.018]; *Not Valuable and Not Scarce*: b = -0.034, SE = 0.017, p = 0.048, 95% CI [-0.068, -0.0002]; Figure C1).

Figure C1. Associations between priority tier placement and explicit bias by student race (Black vs. White) and condition (*Valuable and Scarce* vs. *Not Valuable and Not Scarce*).



Note. Bias scores are raw values (i.e., zero indicates equal preference for Black and White individuals) and are displayed from the minimum to the maximum value in our data.

Non-Preregistered Outcomes

For both outcomes (binary decision and expected performance), the three-way interaction of race, implicit bias, and experimental condition was significant at alpha level of 0.10 (ps < 0.096). Similar to the priority tier decision, this interaction was driven by the two-way interaction of race and implicit bias emerging only in the *Valuable and Scarce* condition (ps < 0.032), with implicit bias associated with more negative evaluations of Black students but not with evaluations of White students. The race x implicit bias interaction was not significant in the *Not Valuable and Not Scarce* condition (ps > 0.562).

Turning to explicit bias, unlike priority tier decision, here we observed patterns similar to implicit bias such that explicit bias differentially predicted student evaluations only in the *Valuable and Scarce* condition. Specifically, the three-way interaction of race, bias, and experimental condition was trending significance (ps < 0.131), and the two-way interaction of race and bias emerged only in the *Valuable and Scarce* condition (ps < 0.078)—driven by explicit bias predicting negative evaluations of Black students more strongly than of White students—and not in the *Not Valuable and Not Scarce* condition (ps > 0.586).

Table C4a. Regression coefficients of implicit bias, race, condition, and their interaction predicting binary decision, followed by simple slopes of bias for each race at average level of qualification (Study 2).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	3.246	0.308	<0.001	2.643	3.850
Race	-0.538	0.281	0.056	-1.089	0.013
Bias	-0.234	0.374	0.533	-0.967	0.500
Condition	0.044	0.483	0.928	-0.904	0.991
Race x Bias	0.488	0.428	0.255	-0.352	1.327
Race x Bias x Condition	1.741	0.858	0.042	0.060	3.422
Race x Bias for Valuable and Scarce	**1.358**	**0.547**	**0.013**	**0.286**	**2.430**
Slope of Bias for Black Students	-1.099	0.583	0.060	-2.241	0.044
Slope of Bias for White Students	0.259	0.521	0.619	-0.763	1.281
Race x Bias for Not Valuable and Not Scarce	**-0.383**	**0.660**	**0.562**	**-1.676**	**0.910**
Slope of Bias for Black Students	0.144	0.672	0.830	-1.173	1.461
Slope of Bias for White Students	-0.239	0.650	0.713	-1.513	1.036

Table C4b. Regression coefficients of explicit bias, race, condition, and their interaction predicting binary decision, followed by simple slopes of bias for each race at average level of qualification (Study 2).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	3.211	0.238	<0.001	2.745	3.677
Race	-0.360	0.190	0.058	-0.732	0.012
Bias	-0.359	0.083	<0.001	-0.521	-0.196
Condition	-0.030	0.308	0.921	-0.633	0.572
Race x Bias	0.090	0.096	0.346	-0.098	0.278
Race x Bias x Condition	0.321	0.192	0.095	-0.056	0.698
Race x Bias for Valuable and Scarce	**0.251**	**0.142**	**0.078**	**-0.028**	**0.530**
Slope of Bias for Black Students	-0.586	0.150	<0.001	-0.880	-0.292
Slope of Bias for White Students	-0.335	0.135	0.013	-0.599	-0.071
Race x Bias for Not Valuable and Not Scarce	**-0.070**	**0.129**	**0.586**	**-0.323**	**0.182**
Slope of Bias for Black Students	-0.222	0.128	0.083	-0.472	0.029
Slope of Bias for White Students	-0.292	0.123	0.018	-0.534	-0.050

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as all lower-level interactions between race, bias, qualification, and condition, were included in the regression but not shown for parsimony. Bolded coefficients highlight the key effects, indicating whether bias differently predicts evaluations of Black versus White students within each condition.

Table C5a. Regression coefficients of implicit bias, race, condition, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Study 2).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	6.970	0.078	<0.001	6.817	7.123
Race	-0.188	0.062	0.003	-0.309	-0.066
Bias	0.045	0.122	0.711	-0.195	0.286
Condition	0.258	0.156	0.099	-0.048	0.564
Race x Bias	0.108	0.097	0.269	-0.084	0.299
Race x Bias x Condition	0.325	0.195	0.096	-0.058	0.708
Race x Bias for Valuable and Scarce	**0.271**	**0.126**	**0.032**	**0.023**	**0.518**
Slope of Bias for Black Students	-0.250	0.167	0.135	-0.579	0.078
Slope of Bias for White Students	0.020	0.174	0.908	-0.321	0.361
Race x Bias for Not Valuable and Not Scarce	**-0.055**	**0.149**	**0.713**	**-0.347**	**0.237**
Slope of Bias for Black Students	0.233	0.197	0.237	-0.154	0.621
Slope of Bias for White Students	0.179	0.205	0.384	-0.224	0.581

Table C5b. Regression coefficients of explicit bias, race, condition, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Study 2).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	7.011	0.049	<0.001	6.916	7.107
Race	-0.146	0.039	<0.001	-0.223	-0.070
Bias	-0.071	0.026	0.007	-0.122	-0.019
Condition	0.099	0.097	0.308	-0.092	0.290
Race x Bias	0.038	0.021	0.068	-0.003	0.079
Race x Bias x Condition	0.063	0.042	0.131	-0.019	0.145
Race x Bias for Valuable and Scarce	**0.070**	**0.032**	**0.028**	**0.007**	**0.132**
Slope of Bias for Black Students	-0.104	0.042	0.013	-0.186	-0.022
Slope of Bias for White Students	-0.034	0.044	0.431	-0.120	0.051
Race x Bias for Not Valuable and Not Scarce	**0.007**	**0.027**	**0.807**	**-0.047**	**0.060**
Slope of Bias for Black Students	-0.075	0.036	0.036	-0.145	-0.005
Slope of Bias for White Students	-0.068	0.037	0.067	-0.142	0.005

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as all lower-level interactions between race, bias, qualification, and condition, were included in the regression but not shown for parsimony. Bolded coefficients highlight the key effects, indicating whether bias differently predicts evaluations of Black versus White students within each condition.

Analyses Excluding Participants Who Failed the Attention and Manipulation Check

For robustness checks, we repeated the analyses excluding participants who failed the attention check (i.e., those who did not recall seeing race or name in the students' materials) and the manipulation check (i.e., those who selected the most inaccurate answer to a question about the scarcity of AP courses at this high school). The results remained consistent with those reported in the main text: The interaction between implicit bias and race was significant only in the *Valuable and Scarce* condition, driven by a negative slope for evaluating Black students. In contrast, the interaction between explicit bias and race was comparable in size across both conditions.

Table C6a. Regression coefficients of implicit bias, race, condition, and their interaction predicting priority tier decision, followed by simple slopes of bias for each race at average level of qualification, excluding participants who failed the attention and manipulation check (Study 2).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	1.548	0.039	<0.001	1.472	1.624
Race	-0.158	0.038	<0.001	-0.233	-0.084
Bias	0.006	0.061	0.926	-0.115	0.127
Condition	0.031	0.077	0.685	-0.121	0.183
Race x Bias	0.124	0.061	0.041	0.005	0.243
Race x Bias x Condition	0.169	0.121	0.162	-0.068	0.407
Race x Bias for Valuable and Scarce	**0.209**	**0.072**	**0.004**	**0.067**	**0.351**
Slope of Bias for Black Students	-0.196	0.082	0.017	-0.356	-0.035
Slope of Bias for White Students	0.013	0.082	0.874	-0.148	0.174
Race x Bias for Not Valuable and Not Scarce	**0.039**	**0.097**	**0.686**	**-0.152**	**0.230**
Slope of Bias for Black Students	0.083	0.110	0.449	-0.133	0.299
Slope of Bias for White Students	0.122	0.110	0.268	-0.094	0.339

Table C6b. Regression coefficients of explicit bias, race, condition, and their interaction predicting priority tier decision, followed by simple slopes of bias for each race at average level of qualification, excluding participants who failed the attention and manipulation check (Study 2).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	1.560	0.024	<0.001	1.514	1.607
Race	-0.106	0.023	<0.001	-0.152	-0.060
Bias	-0.030	0.013	0.017	-0.055	-0.005
Condition	-0.063	0.047	0.183	-0.156	0.030
Race x Bias	0.026	0.012	0.038	0.001	0.050
Race x Bias x Condition	0.003	0.025	0.893	-0.045	0.052
Race x Bias for Valuable and Scarce	**0.028**	**0.018**	**0.120**	**-0.007**	**0.062**
Slope of Bias for Black Students	-0.045	0.020	0.022	-0.084	-0.006
Slope of Bias for White Students	-0.018	0.020	0.372	-0.057	0.021
Race x Bias for Not Valuable and Not Scarce	**0.024**	**0.017**	**0.165**	**-0.010**	**0.058**
Slope of Bias for Black Students	-0.041	0.020	0.039	-0.079	-0.002
Slope of Bias for White Students	-0.016	0.020	0.409	-0.055	0.022

Note. Only participants who passed the attention and manipulation check were included ($N = 206$ and 255 for the *Not Valuable and Not Scarce* and the *Valuable and Scarce* condition, respectively). Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = - 0.5), as well as all lower-level interactions between race, bias, qualification, and condition, were included in the regression but not shown for parsimony. Bolded coefficients highlight the key effects, indicating whether bias differently predicts evaluations of Black versus White students within each condition.

Analyzing Data as Between-Subject

As in Study 1, we re-ran the analyses using only the second application (i.e., the first application participants reviewed after the highly qualified student) to address potential concerns about participants adjusting their ratings over time. Participants whose second application featured a Black or White students were included ($N_{\text{Valuable and Scarce}} = 214$, $N_{\text{Not Valuable and Not Scarce}} = 219$). Likely due to the reduced statistical power of the between-subjects design, the interaction between implicit bias and student race in the *Valuable and Scarce* condition was no longer significant ($p = 0.190$). However, the pattern remained directionally consistent with the within-subjects analysis, such that greater implicit bias was associated with marginally lower ratings for Black students ($p = 0.094$) but not with ratings for White students ($p = 0.982$). The interaction between implicit bias and student race in the *Not Valuable and Not Scarce* condition remained non-significant ($p = 0.471$).

Table C7a. Regression coefficients of implicit bias, race, condition, and their interaction predicting priority tier decision, followed by simple slopes of bias for each race at average level of qualification, treating data as between-subject (Study 2).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	1.580	0.057	<0.001	1.467	1.693
Race	-0.368	0.115	0.001	-0.594	-0.142
Bias	0.028	0.091	0.759	-0.151	0.207
Condition	0.131	0.115	0.254	-0.094	0.357
Race x Bias	0.258	0.182	0.157	-0.100	0.616
Race x Bias x Condition	0.128	0.364	0.725	-0.587	0.843
Race x Bias for Valuable and Scarce	**0.322**	**0.245**	**0.190**	**-0.160**	**0.804**
Slope of Bias for Black Students	-0.318	0.189	0.094	-0.691	0.054
Slope of Bias for White Students	0.004	0.156	0.982	-0.303	0.310
Race x Bias for Not Valuable and Not Scarce	**0.194**	**0.269**	**0.471**	**-0.334**	**0.722**
Slope of Bias for Black Students	0.116	0.205	0.572	-0.287	0.520
Slope of Bias for White Students	0.310	0.173	0.074	-0.031	0.651

Table C7b. Regression coefficients of explicit bias, race, condition, and their interaction predicting priority tier decision, followed by simple slopes of bias for each race at average level of qualification, treating data as between-subject (Study 2).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	1.615	0.034	<0.001	1.548	1.681
Race	-0.269	0.068	<0.001	-0.403	-0.136
Bias	-0.062	0.023	0.007	-0.108	-0.017
Condition	-0.045	0.068	0.505	-0.179	0.088
Race x Bias	0.078	0.046	0.094	-0.013	0.168
Race x Bias x Condition	-0.028	0.092	0.762	-0.210	0.154
Race x Bias for Valuable and Scarce	**0.064**	**0.075**	**0.394**	**-0.083**	**0.210**
Slope of Bias for Black Students	-0.144	0.059	0.015	-0.261	-0.028
Slope of Bias for White Students	-0.081	0.045	0.077	-0.170	0.009
Race x Bias for Not Valuable and Not Scarce	**0.092**	**0.054**	**0.093**	**-0.015**	**0.199**
Slope of Bias for Black Students	-0.058	0.036	0.111	-0.129	0.013
Slope of Bias for White Students	0.034	0.041	0.408	-0.046	0.113

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as all lower-level interactions between race, bias, qualification, and condition, were included in the regression but not shown for parsimony. Bolded coefficients highlight the key effects, indicating whether bias differently predicts evaluations of Black versus White students within each condition.

STUDY 3

Explicit Bias

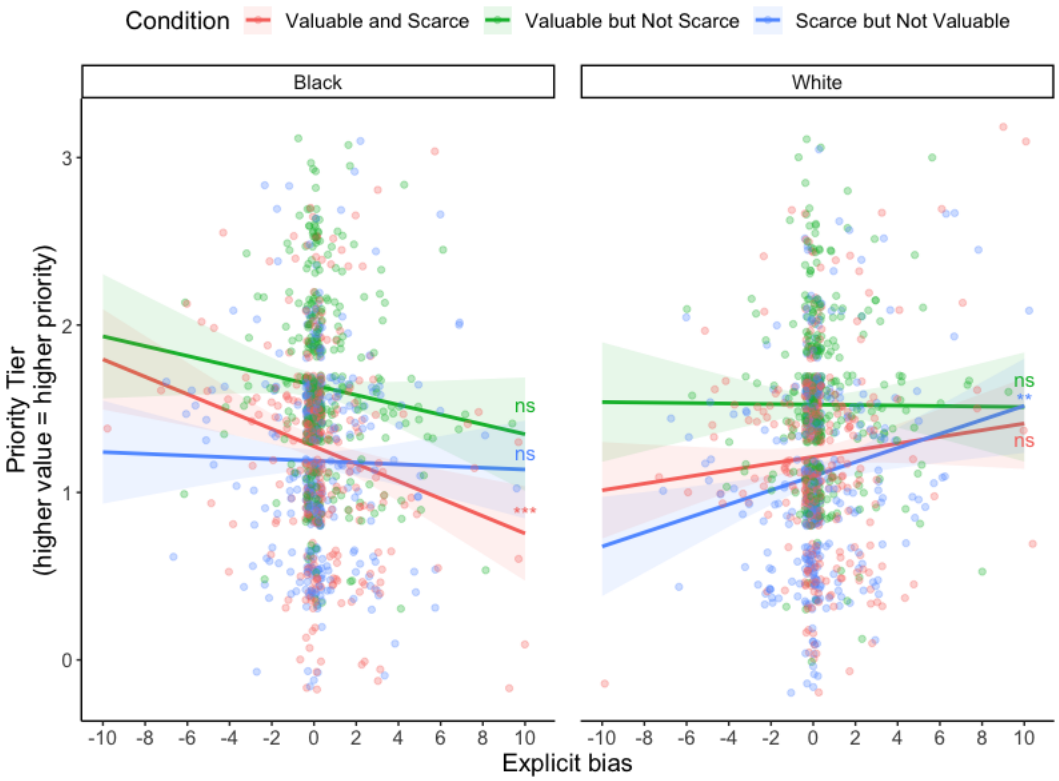
Priority Tier Decision

In this sample, the main effect of explicit bias was not significant (b = -0.004, SE = 0.008, p = 0.592, 95% CI [-0.020, 0.012]), but the main effect of race was (b = -0.090, SE = 0.015, p < 0.001, 95% CI [-0.119, -0.060]), again with White students placed into lower priority tiers than Black students. Similar to Studies 1 and 2, this main effect was qualified by a significant interaction between explicit bias and race (b = 0.049, SE = 0.008, p < 0.001, 95% CI [0.033, 0.064])—this time driven by more explicitly biased people both deprioritizing Black students (b = -0.029, SE = 0.009, p = 0.002, 95% CI [-0.047, -0.011]) and prioritizing White students (b = 0.020, SE = 0.009, p = 0.022, 95% CI [0.003, 0.037]).

Unlike implicit bias, this two-way interaction emerged consistently across all three conditions (*Valuable and Scarce*: b = 0.072, SE = 0.013, p < 0.001, 95% CI [0.047, 0.096]; *Valuable but Not Scarce*: b = 0.028, SE = 0.015, p = 0.071, 95% CI [-0.002, 0.058]; *Scarce but Not Valuable*: b = 0.047, SE = 0.013, p < 0.001, 95% CI [0.022, 0.073]). For the two *Valuable* conditions, the interaction was largely driven by more explicitly biased participants deprioritizing Black students (ps < 0.101) but not White students (ps > 0.154); for the *Scarce but Not Valuable* condition, it was driven by more explicitly biased participants prioritizing White students (p = 0.004) but not Black students (p = 0.729; Figure C2).

Overall, these results are consistent with Study 2: explicit bias generally predicted biased decisions, whereas implicit bias did so only when the opportunity was described as both valuable and scarce.

Figure C2. Associations between priority tier placement and explicit bias by student race (Black vs. White) and condition (*Valuable and Scarce* vs. *Valuable but Not Scarce* vs. *Not Valuable and Not Scarce*).



Note. Bias scores are raw values (i.e., zero indicates equal preference for Black and White individuals) and are displayed from the minimum to the maximum value in our data.

Non-Preregistered Outcomes

For implicit bias, results were similar to the priority tier decision: The two-way interaction of race and implicit bias emerged only in the *Valuable and Scarce* condition (*p*s < 0.059). For the continuous outcome (expected performance), this interaction was again driven by implicit bias predicting less favorable evaluations of Black students ($p = 0.021$) but not White students ($p = 0.749$). The race x implicit bias interaction was not significant in either the *Valuable but Not Scarce* condition (*p*s > 0.308) or the *Scarce but Not Valuable* condition (*p*s > 0.184).

For explicit bias, results for the continuous outcome (expected performance) also paralleled the priority tier decision: The two-way interaction of race and explicit bias emerged consistently across all conditions (*p*s < 0.007), driven by explicit bias predicting less favorable evaluations of Black students (*p*s < 0.009) but not White students (*p*s > 0.365). For the binary decision, the two-way interaction of race and explicit bias appeared in the two Scarce conditions (*p*s < 0.010)—again driven by negative slopes of explicit bias when evaluating Black students—but not in the *Valuable but Not Scarce* condition ($p = 0.836$). Overall, the extent to which explicit bias differentially predicts student evaluations is less influenced by context than implicit bias.

Table C8a. Regression coefficients of implicit bias, race, condition, and their interaction predicting binary decision, followed by simple slopes of bias for each race at average level of qualification (Study 3).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	3.006	0.213	<0.001	2.589	3.423
Race	-0.575	0.222	0.010	-1.010	-0.139
Bias	-0.242	0.285	0.397	-0.801	0.318
Valuable and Scarce	-1.093	0.236	<0.001	-1.555	-0.632
Valuable but Not Scarce	2.193	0.294	<0.001	1.617	2.769
Race x Bias	0.323	0.362	0.372	-0.386	1.032
Race x Bias x Valuable and Scarce	0.492	0.439	0.263	-0.369	1.353
Race x Bias x Valuable but Not Scarce	-0.453	0.629	0.471	-1.687	0.780
Race x Bias for Valuable and Scarce	**0.815**	**0.432**	**0.059**	**-0.031**	**1.661**
Slope of Bias for Black Students	-0.405	0.474	0.393	-1.334	0.524
Slope of Bias for White Students	0.410	0.463	0.375	-0.497	1.317
Race x Bias for Valuable but Not Scarce	**-0.130**	**0.892**	**0.884**	**-1.878**	**1.617**
Slope of Bias for Black Students	0.059	0.851	0.945	-1.608	1.726
Slope of Bias for White Students	-0.072	0.667	0.914	-1.380	1.236
Race x Bias for Scarce but Not Valuable	**0.285**	**0.443**	**0.521**	**-0.584**	**1.153**
Slope of Bias for Black Students	-0.863	0.486	0.076	-1.816	0.090
Slope of Bias for White Students	-0.578	0.460	0.208	-1.479	0.323

Table C8b. Regression coefficients of explicit bias, race, condition, and their interaction predicting binary decision, followed by simple slopes of bias for each race at average level of qualification (Study 3).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	2.978	0.170	<0.001	2.645	3.310
Race	-0.521	0.153	0.001	-0.820	-0.222
Bias	-0.100	0.064	0.120	-0.226	0.026
Valuable and Scarce	-0.979	0.163	<0.001	-1.299	-0.659
Valuable but Not Scarce	2.331	0.212	<0.001	1.915	2.748
Race x Bias	0.170	0.083	0.041	0.007	0.334
Race x Bias x Valuable and Scarce	0.047	0.096	0.624	-0.141	0.235
Race x Bias x Valuable but Not Scarce	-0.126	0.150	0.401	-0.419	0.168
Race x Bias for					
Valuable and Scarce	**0.217**	**0.083**	**0.009**	**0.055**	**0.380**
Slope of Bias for Black Students	-0.221	0.094	0.019	-0.406	-0.037
Slope of Bias for White Students	-0.004	0.093	0.967	-0.186	0.178
Race x Bias for					
Valuable but Not Scarce	**0.045**	**0.215**	**0.836**	**-0.378**	**0.467**
Slope of Bias for Black Students	-0.134	0.207	0.517	-0.541	0.272
Slope of Bias for White Students	-0.090	0.156	0.565	-0.395	0.216
Race x Bias for					
Scarce but Not Valuable	**0.249**	**0.096**	**0.010**	**0.060**	**0.438**
Slope of Bias for Black Students	-0.200	0.104	0.054	-0.403	0.004
Slope of Bias for White Students	0.049	0.100	0.623	-0.147	0.246

Note: Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as all lower-level interactions between race, bias, qualification, and condition, were included in the regression but not shown for parsimony. Bolded coefficients highlight the key effects, indicating whether bias differently predicts evaluations of Black versus White students within each condition.

Table C9a. Regression coefficients of implicit bias, race, condition, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Study 3).

	b	***SE***	***p-value***	***Lower CI***	***Upper CI***
Intercept	6.973	0.056	<0.001	6.863	7.083
Race	-0.125	0.045	0.005	-0.213	-0.038
Bias	-0.284	0.089	0.002	-0.460	-0.109
Valuable and Scarce	-0.163	0.078	0.038	-0.316	-0.009
Valuable but Not Scarce	0.534	0.081	<0.001	0.375	0.693
Race x Bias	0.121	0.071	0.090	-0.019	0.260
Race x Bias x Valuable and Scarce	0.210	0.099	0.035	0.015	0.404
Race x Bias x Valuable but Not Scarce	-0.251	0.102	0.014	-0.452	-0.050
Race x Bias for Valuable and Scarce	**0.330**	**0.120**	**0.006**	**0.095**	**0.566**
Slope of Bias for Black Students	-0.382	0.165	0.021	-0.705	-0.059
Slope of Bias for White Students	-0.051	0.160	0.749	-0.365	0.263
Race x Bias for Valuable but Not Scarce	**-0.130**	**0.128**	**0.308**	**-0.380**	**0.120**
Slope of Bias for Black Students	-0.352	0.175	0.044	-0.695	-0.009
Slope of Bias for White Students	-0.482	0.170	0.005	-0.815	-0.149
Race x Bias for Scarce but Not Valuable	**0.162**	**0.122**	**0.184**	**-0.077**	**0.400**
Slope of Bias for Black Students	-0.301	0.167	0.072	-0.629	0.027
Slope of Bias for White Students	-0.139	0.162	0.392	-0.457	0.179

Table C9b. Regression coefficients of explicit bias, race, condition, and their interaction predicting expected performance, followed by simple slopes of bias for each race at average level of qualification (Study 3).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	6.857	0.037	<0.001	6.784	6.930
Race	-0.111	0.029	<0.001	-0.167	-0.054
Bias	-0.055	0.019	0.005	-0.093	-0.017
Valuable and Scarce	-0.128	0.052	0.014	-0.231	-0.026
Valuable but Not Scarce	0.479	0.053	<0.001	0.375	0.583
Race x Bias	0.123	0.015	<0.001	0.094	0.153
Race x Bias x Valuable and Scarce	0.046	0.020	0.022	0.007	0.086
Race x Bias x Valuable but Not Scarce	-0.044	0.023	0.051	-0.088	0.000
Race x Bias for Valuable and Scarce	**0.170**	**0.024**	**<0.001**	**0.123**	**0.216**
Slope of Bias for Black Students	-0.147	0.033	<0.001	-0.212	-0.081
Slope of Bias for White Students	0.023	0.033	0.485	-0.041	0.087
Race x Bias for Valuable but Not Scarce	**0.079**	**0.029**	**0.007**	**0.022**	**0.136**
Slope of Bias for Black Students	-0.113	0.041	0.006	-0.194	-0.033
Slope of Bias for White Students	-0.034	0.040	0.395	-0.113	0.045
Race x Bias for Scarce but Not Valuable	**0.121**	**0.025**	**<0.001**	**0.073**	**0.169**
Slope of Bias for Black Students	-0.090	0.034	0.009	-0.157	-0.022
Slope of Bias for White Students	0.031	0.034	0.365	-0.036	0.097

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as all lower-level interactions between race, bias, qualification, and condition, were included in the regression but not shown for parsimony. Bolded coefficients highlight the key effects, indicating whether bias differently predicts evaluations of Black versus White students within each condition.

Analyses Including Implicit and Explicit Bias Simultaneously

Since implicit and explicit bias were weakly correlated ($r = 0.16$), we entered them simultaneously in the regression (as we initially preregistered). The overall results were consistent with those reported in the main text but weaker for implicit bias, likely because explicit bias absorbed some of its explanatory power. Specifically, implicit bias no longer differentially predicted priority tier decisions in the *Valuable and Scarce* condition (two-way interaction of race and implicit bias: $p = 0.212$), but it still predicted lower tier placement for Black students ($p = 0.031$)—a pattern not observed in the other two conditions. Explicit bias continued to differentially predict priority tier decisions across all conditions (ps < 0.072).

Table C10. Regression coefficients of implicit and explicit bias, race, condition, and their interaction predicting priority tier decision, followed by simple slopes of bias for each race at average level of qualification (Study 3).

	b	*SE*	*p-value*	*Lower CI*	*Upper CI*
Intercept	1.365	0.023	<0.001	1.319	1.410
Race	-0.099	0.023	<0.001	-0.144	-0.054
Implicit Bias	-0.089	0.037	0.018	-0.162	-0.015
Explicit Bias	-0.002	0.008	0.850	-0.018	0.014
Valuable and Scarce	-0.068	0.032	0.037	-0.131	-0.004
Valuable but Not Scarce	0.265	0.034	<0.001	0.199	0.331
Race x Implicit Bias	0.020	0.037	0.582	-0.052	0.092
Race x Implicit Bias x Valuable and Scarce	0.057	0.051	0.265	-0.044	0.158
Race x Implicit Bias x Valuable but Not Scarce	-0.024	0.053	0.650	-0.127	0.079
Race x Implicit Bias for Valuable and Scarce	**0.078**	**0.062**	**0.212**	**-0.044**	**0.199**
Slope of Bias for Black Students	-0.155	0.072	0.031	-0.296	-0.015
Slope of Bias for White Students	-0.078	0.069	0.261	-0.214	0.058
Race x Implicit Bias for Valuable but Not Scarce	**-0.004**	**0.065**	**0.955**	**-0.132**	**0.124**
Slope of Bias for Black Students	-0.095	0.076	0.207	-0.243	0.053
Slope of Bias for White Students	-0.099	0.073	0.174	-0.242	0.044
Race x Implicit Bias for Scarce but Not Valuable	**-0.013**	**0.063**	**0.836**	**-0.138**	**0.111**
Slope of Bias for Black Students	-0.046	0.073	0.531	-0.190	0.098
Slope of Bias for White Students	-0.059	0.071	0.404	-0.198	0.080
Race x Explicit Bias	0.048	0.008	<0.001	0.033	0.064
Race x Explicit Bias x Valuable and Scarce	0.021	0.011	0.054	0.000	0.042
Race x Explicit Bias x Valuable but Not Scarce	-0.020	0.012	0.088	-0.044	0.003
Race x Explicit Bias for Valuable and Scarce	**0.069**	**0.013**	**<0.001**	**0.044**	**0.094**
Slope of Bias for Black Students	-0.047	0.015	0.001	-0.075	-0.018
Slope of Bias for White Students	0.023	0.014	0.111	-0.005	0.050
Race x Explicit Bias for Valuable but Not Scarce	**0.028**	**0.015**	**0.072**	**-0.002**	**0.058**
Slope of Bias for Black Students	-0.027	0.018	0.129	-0.062	0.008
Slope of Bias for White Students	0.001	0.017	0.968	-0.033	0.034

Race x Explicit Bias for Scarce but Not Valuable	**0.048**	**0.013**	**<0.001**	**0.022**	**0.074**
Slope of Bias for Black Students	-0.003	0.015	0.832	-0.033	0.027
Slope of Bias for White Students	0.045	0.015	0.003	0.016	0.073

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as all lower-level interactions between race, bias, qualification, and condition, were included in the regression but not shown for parsimony. Bolded coefficients highlight the key effects, indicating whether bias differently predicts evaluations of Black versus White students within each condition.

Analyzing Data as Between-Subject

Participants whose second application featured a Black or White students were included ($N_{\text{Valuable and Scarce}} = 295$, $N_{\text{Valuable but Not Scarce}} = 279$, $N_{\text{Scarce but Not Valuable}} = 271$). Consistent with the within-subject analysis, a significant interaction between implicit bias and student race was observed only in the *Valuable and Scarce* condition ($p = 0.002$). Simple slope analyses indicated that greater implicit bias was associated with placing Black students into lower priority tiers ($p = 0.016$) and White students into higher priority tiers ($p = 0.045$). In contrast, the interaction between implicit bias and student race in the *Valuable but Not Scarce* and *Scarce but Not Valuable* conditions remained non-significant (ps > 0.396).

Table C11a. Regression coefficients of implicit bias, race, condition, and their interaction predicting priority tier decision, followed by simple slopes of bias for each race at average level of qualification, treating data as between-subject (Study 3).

	b	***SE***	***p-value***	***Lower CI***	***Upper CI***
Intercept	1.362	0.036	<0.001	1.291	1.433
Race	-0.263	0.073	<0.001	-0.406	-0.121
Bias	-0.044	0.059	0.453	-0.159	0.071
Valuable and Scarce	-0.114	0.050	0.024	-0.212	-0.015
Valuable but Not Scarce	0.238	0.052	<0.001	0.136	0.340
Race x Bias	0.216	0.117	0.065	-0.014	0.446
Race x Bias x Valuable and Scarce	0.396	0.164	0.016	0.074	0.718
Race x Bias x Valuable but Not Scarce	-0.353	0.167	0.034	-0.680	-0.026
Race x Bias for Valuable and Scarce	**0.612**	**0.199**	**0.002**	**0.221**	**1.003**
Slope of Bias for Black Students	-0.298	0.124	0.016	-0.541	-0.056
Slope of Bias for White Students	0.314	0.156	0.045	0.008	0.620
Race x Bias for Valuable but Not Scarce	**-0.137**	**0.205**	**0.504**	**-0.540**	**0.266**
Slope of Bias for Black Students	0.026	0.154	0.865	-0.275	0.328
Slope of Bias for White Students	-0.111	0.136	0.415	-0.378	0.156
Race x Bias for Scarce but Not Valuable	**0.173**	**0.204**	**0.396**	**-0.227**	**0.574**
Slope of Bias for Black Students	-0.184	0.152	0.228	-0.483	0.115
Slope of Bias for White Students	-0.010	0.136	0.939	-0.277	0.256

Table C11b. Regression coefficients of explicit bias, race, condition, and their interaction predicting priority tier decision, followed by simple slopes of bias for each race at average level of qualification, treating data as between-subject (Study 3).

	b	***SE***	***p-value***	***Lower CI***	***Upper CI***
Intercept	1.346	0.024	<0.001	1.299	1.394
Race	-0.173	0.048	<0.001	-0.269	-0.078
Bias	-0.005	0.014	0.740	-0.033	0.023
Valuable and Scarce	-0.095	0.034	0.005	-0.161	-0.029
Valuable but Not Scarce	0.259	0.035	<0.001	0.190	0.327
Race x Bias	0.036	0.029	0.210	-0.020	0.092
Race x Bias x Valuable and Scarce	0.055	0.04	0.163	-0.022	0.133
Race x Bias x Valuable but Not Scarce	-0.075	0.043	0.082	-0.160	0.010
Race x Bias for					
Valuable and Scarce	**0.091**	**0.048**	**0.056**	**-0.002**	**0.185**
Slope of Bias for Black Students	-0.040	0.039	0.297	-0.116	0.036
Slope of Bias for White Students	0.051	0.028	0.069	-0.004	0.106
Race x Bias for					
Valuable but Not Scarce	**-0.039**	**0.056**	**0.483**	**-0.150**	**0.071**
Slope of Bias for Black Students	-0.026	0.035	0.459	-0.094	0.042
Slope of Bias for White Students	-0.065	0.044	0.141	-0.152	0.022
Race x Bias for					
Scarce but Not Valuable	**0.056**	**0.044**	**0.202**	**-0.030**	**0.141**
Slope of Bias for Black Students	-0.002	0.033	0.957	-0.067	0.064
Slope of Bias for White Students	0.054	0.028	0.055	-0.001	0.109

Note. Student qualification (sum-to-zero coded as *Moderate* = 0.5, *Low* = -0.5), as well as all lower-level interactions between race, bias, qualification, and condition, were included in the regression but not shown for parsimony. Bolded coefficients highlight the key effects, indicating whether bias differently predicts evaluations of Black versus White students within each condition.

Mediation Analyses

In addition to testing moderation (i.e., in which experimental condition the relationship between implicit bias and biased decision-making is observed), we considered different psychological mechanisms that could explain *why* the value, scarcity, or their combination would result in implicit bias predicting biased decision-making. We tested three competing accounts:

Scarcity-Competition

This account postulates that implicit bias will yield biased decision-making when the contested opportunity concerns scarce resources that elicit greater intergroup competition and ingroup favoritism (Sherif, 1966). Resource scarcity has been shown to be associated with worse economic outcomes for Black people (Bianchi et al., 2018; Chattopadhyay & Bianchi, 2021) as well as more biased processing of visual stimuli (e.g., perceiving Black faces as "Blacker"; (Krosch & Amodio, 2014; Rodeheffer et al., 2012) and greater expression of stereotypes of Black people as low-SES and threatening (Berkebile-Weinberg et al., 2022). Taken together, these findings point to the possibility that when people perceive greater competition over scarce resources, they are motivated to engage in facial and cognitive processing consistent with their biases to justify discrimination.

Value-Feeling Good

This account suggests that implicit bias will yield biased decision-making when the opportunity concerns valuable resources that people feel good about the possibility of gaining. Positive mood has been shown to serve as a "go signal" that promotes the use of easily accessible processing tendencies, such as implicit biases (Ray & Huntsinger, 2017), such that people's behaviors are more strongly influenced by their implicit biases when they are in a

positive mood than in a negative mood (Holland et al., 2012). Thus, this research suggests that positive mood stemming from exposure to valuable resources may facilitate biased cognitive processing that justifies discriminating to attain said resources.

Combination-Anxiety/Group Status Threat

This account asserts that implicit bias will yield biased decision-making only when the opportunity concerns valuable and scarce resources. Valuable and scarce opportunities may uniquely induce anxiety about not securing them (Roda & Wells, 2013; Sattin-Bajaj & Roda, 2020), unlike opportunities that are valuable but abundant (which are easier to obtain) or scarce but low-value (which carry lower stakes). Similarly, resource competition heightens intergroup threat (Sherif, 1966), and this effect may be amplified when the competition involves opportunities that are both difficult to obtain and significantly enhance group status once secured. The MODE model of the attitude-behavior relations suggests that implicit attitudes are most predictive of behaviors when motivation and opportunity for self-regulation are low (Fazio & Olson, 2014; Friese et al., 2008). Together, if heightened anxiety and perceived threat dampen motivation to regulate biases, implicit bias may become more predictive of behavior, escalating biased decision-making when decisions concern highly valuable and scarce opportunities.

Measures

All measures were completed after participants read about the AP program but before they reviewed the application materials, except for the group status threat measure, which was administered afterward to minimize social desirability concerns during decision-making.

Perceived Scarcity

Participants completed one item assessing their perception of scarcity ("How scarce is the opportunity to take AP courses at this high school?") on a scale of 1 = *Not scarce at all* to 5 = *Very scarce.*

Mood

Participants reported the extent to which they experienced the following feelings when reading about the AP program on a scale of 1 = *Not at all* to 5 = *Very much*: positive, negative, happy, sad (Huntsinger et al., 2009). The ratings were recoded as needed and averaged to create a composite score of mood, such that higher values indicate more positive affect (Cronbach's α = 0.85).

Anxiety

Participants completed the arousal subscale from the Self-Assessment Manikin (Bradley & Lang, 1994). Specifically, they were asked to imagine that their child or children (or an imaginary one, if they do not have one) attend(s) this high school and wants to take AP courses. They then reported how anxious they would feel about the chances of their child(ren) not being accepted into AP courses by selecting one of the five images, ranging from a 1 = not aroused figure to 5 = highly aroused figure.

Group Status Threat

Participants completed two items assessing perceived status threat posed by the presence of racial minority students in AP classrooms (e.g., "Ethnic minority students in AP classrooms would threaten my ethnic group's status") on a scale of 1 = *Strongly Disagree* to 5 = *Strongly Agree.*

Results

Effects of Experimental Condition on Mediators

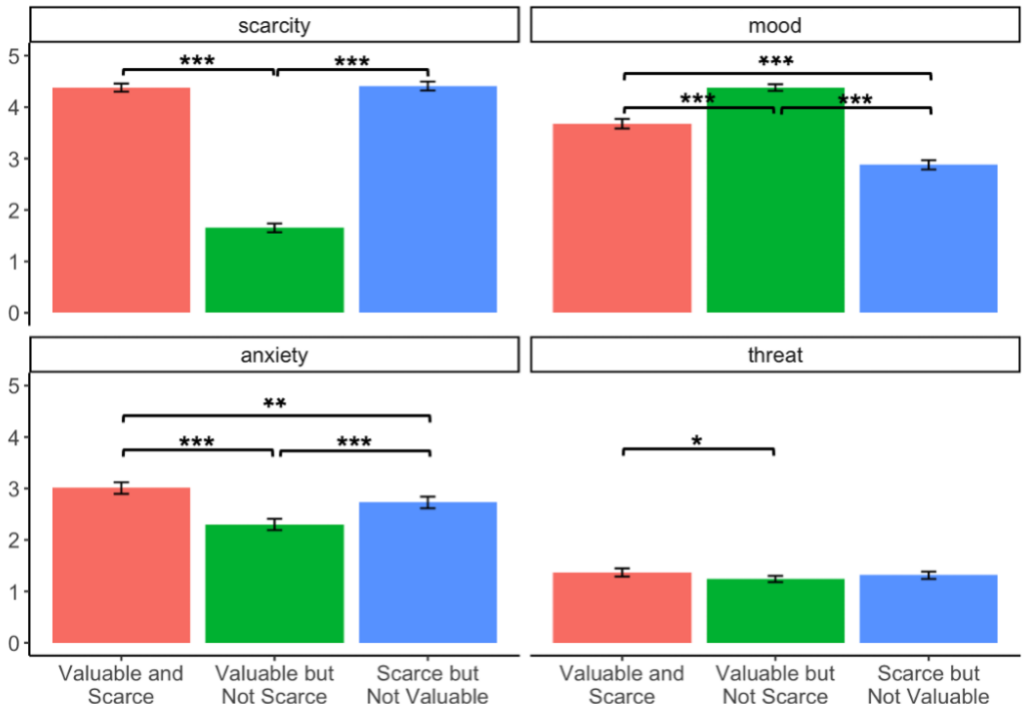
Perceived Scarcity. The manipulation was successful at changing perceptions of AP course scarcity ($F(2, 1052) = 1368$, $p < 0.001$). As expected, both *Valuable and Scarce* ($M = 4.38$, $SD = 0.77$) and *Scarce but Not Valuable* ($M = 4.41$, $SD = 0.83$) conditions differed significantly from the *Valuable but Not Scarce* condition ($M = 1.65$, $SD = 0.81$, $ps < 0.001$), but not from each other ($p = 0.865$; Figure C3, top left panel).

Mood. The manipulation was successful at changing how positively participants felt while reading about the AP program ($F(2, 1052) = 304.5$, $p < 0.001$). Participants felt most positive when the AP program was described as *Valuable but Not Scarce* ($M = 4.38$, $SD = 0.62$), followed by *Valuable and Scarce* ($M = 3.68$, $SD = 0.90$), and least positive when described as *Scarce but Not Valuable* ($M = 2.88$, $SD = 0.86$), all pairwise comparisons significant ($ps < 0.001$; Figure C3, top right panel).

Anxiety. The manipulation was successful at changing how anxious participants felt about the chances that their child(ren) not being accepted into AP courses ($F(2, 1051) = 39.5$, $p < 0.001$). Participants reported feeling most anxious in the *Valuable and Scarce* condition ($M = 3.01$, $SD = 1.08$), followed by the *Scarce but Not Valuable* condition ($M = 2.73$, $SD = 1.07$), followed by the *Valuable but Not Scarce* condition ($M = 2.30$, $SD = 1.03$), all pairwise comparisons significant ($ps < 0.001$; Figure C3, bottom left panel).

Group Status Threat. The manipulation was successful at participants' perception of their group status threat ($F(2, 1052) = 3.1$, $p = 0.045$). Specifically, participants in the *Valuable and Scarce* condition ($M = 1.37$, $SD = 0.77$) reported heightened threat than participants in the *Valuable but Not Scarce* condition ($M = 1.24$, $SD = 0.57$, $p = 0.035$). Participants in the *Scarce but Not Valuable* condition ($M = 1.31$, $SD = 0.67$) did not differ significantly from either of the Valuable conditions ($ps > 0.344$; Figure C3, bottom right panel).

Figure C3. Effects of experimental conditions on proposed mediators (perceived scarcity, positive mood, anxiety, group status threat).



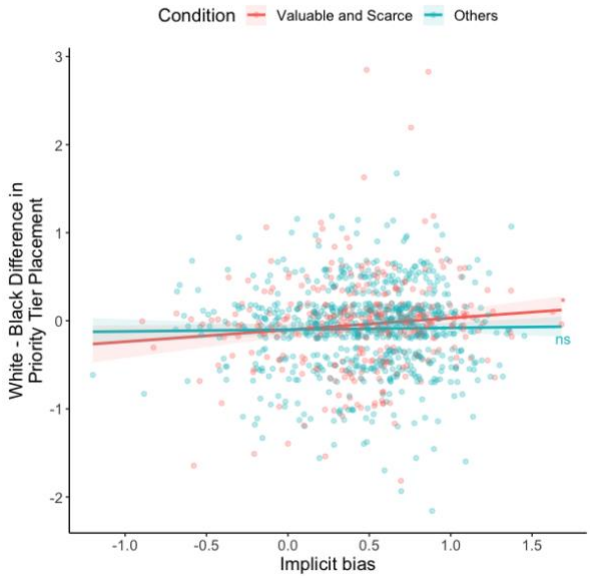
Moderated Mediation Analysis

We sought to better understand how implicit bias leads to biased decisions when the opportunity involves resources that are both valuable and scarce but not when either attribute is absent. To reduce model complexity, we preregistered two modifications to the main analysis. First, we used White-Black differences in priority tier ratings as the outcome, rather than using priority tier ratings as the outcome and race as a moderator. The difference score was calculated as the average of differences in ratings of moderately-qualified White/Black student, and of low-qualified White/Black student, with positive values indicating a preference of White over Black students. Second, given that implicit bias predicted biased decisions only in the *Valuable and Scarce* condition, the other two conditions (*Valuable but Not Scarce, Scarce but Not Valuable*) were collapsed into one condition and used as a reference group.

We first assessed whether implicit bias predicts White-Black differences in priority tier ratings differently in the *Valuable and Scarce* condition versus *Others* (i.e., whether there is a total effect of implicit bias x condition interaction to be mediated). The two-way interaction of implicit bias and condition (analogous to the three-way interaction of implicit bias, condition, and race in the main analysis) was not statistically significant, but directionally aligned with our hypothesis (b = 0.114, SE = 0.077, p = 0.142, 95% CI [-0.038, 0.266]). Specifically, implicit bias predicted greater preferences for White students in the *Valuable and Scarce* condition (b = 0.134, SE = 0.062, p = 0.032, 95% CI [0.012, 0.257]), but not in the *Others* condition (b = 0.020, SE = 0.046, p = 0.658, 95% CI [-0.070, 0.110]; Figure C4).

Although the total interaction of implicit bias and experimental condition was not significant, we followed up with a moderated mediation analysis, examining whether it could be explained by the interaction between implicit bias and anxiety and/or group status threat. We modeled the experimental condition as the predictor, anxiety and group status threat as mediators, implicit bias as the moderator at the *b*- and *c*-paths, and White-Black differences in priority tier ratings as the outcome. This setup was necessary because the experimental condition increased anxiety and group status threat, not implicit bias. However, for consistency with our conceptualization (treating implicit bias as a predictor of biased decision-making), we report how the effect of implicit bias varied across different levels of anxiety and group status threat.

Figure C4. Associations between White-Black difference in priority tier ratings and implicit bias by condition (Valuable and Scarce vs. Others).



Note. Bias scores are raw values (i.e., zero indicates equal preference for Black and White individuals) and are displayed from the minimum to the maximum value in our data.

Anxiety. As hypothesized, participants in the *Valuable and Scarce* condition reported significantly greater anxiety about their child(ren) potentially not getting into AP courses compared to the *Others* condition ($b = 0.448$, $SE = 0.064$, $p < 0.001$, 95% CI [0.323, 0.574]). However, there was no evidence of an interaction between implicit bias and anxiety ($b = 0.003$, $SE = 0.015$, $p = 0.858$, 95% CI [-0.026, 0.032]), resulting in a non-significant moderated mediation ($b = 0.002$, $SE = 0.013$, $p = 0.860$, 95% CI [-0.024, 0.029]). Unpacking this null interaction found that implicit bias did not significant predict greater preferences for White over Black students at either high (i.e., 1 SD above the mean; $b = 0.014$, $SE = 0.010$, $p = 0.141$, 95% CI [-0.004, 0.033]) or low (i.e., 1 SD below the mean; $b = 0.012$, $SE = 0.010$, $p = 0.246$, 95% CI [-0.008, 0.032]) levels of anxiety.

Group Status Threat. Participants in the *Valuable and Scarce* condition reported marginally higher group status threat in response to the presence of ethnic minority students in AP classrooms compared to the *Others* condition ($b = 0.134$, $SE = 0.070$, $p = 0.056$, 95% CI [-

0.0003, 0.272]). Similar to anxiety, however, there was no evidence of an interaction between implicit bias and threat (b = 0.007, SE = 0.027, p = 0.807, 95% CI [-0.045, 0.061]), resulting in a non-significant moderated mediation (b = 0.002, SE = 0.009, p = 0.835, 95% CI [-0.014, 0.022]). Unpacking this null interaction found that implicit bias did not significant predict greater preferences for White over Black students at either high (b = 0.008, SE = 0.008, p = 0.313, 95% CI [-0.002, 0.029]) or low (b = 0.007, SE = 0.006, p = 0.285, 95% CI [-0.002, 0.022]) levels of threat.