High School Role Models and Minority College Achievement*

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Abstract

Large racial differences persist in college enrollment and major choice, which may be exacerbated by the racial distribution of high school teachers. I present the first evidence of the effect of high school students matching with same-race teachers on college outcomes. I also extend the literature on long-run effects of race-matching by presenting the first evidence on Hispanic and Asian students. To address endogenous sorting of students and teachers, I use detailed Texas administrative data on classroom assignment, exploiting variation in student and teacher race within the same course, year, and school, eliminating 99% of observed same-race sorting. Race-matching raises minority students' course performance as well as improves longer-term outcomes like high school graduation and college enrollment. Black and Hispanic students matching with a same-race teacher in a given subject also become more likely to major in that subject in college. Finally, I do not find any robust, significant effects of race-matching for White students, suggesting policies to make the teaching population more representative would likely benefit minority students with minimal negative trade-offs impacting the White student population.

JEL Codes: I21, I23, I24

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1 Introduction

Educational outcomes have unequal distributions across race and income. The difference in college enrollment and completion between high- and low-income families has grown larger over time (Bailey and Dynarski, 2011). While education may be described as a great equalizer, it can also contribute to and widen racial inequalities. Fryer Jr and Levitt (2004) show that Black and White students enter school with similar test scores in reading and math but each year in school widens the gap by 0.1 standard deviations.

One hypothesis for these racial gaps in test scores is the interaction of teachers' and students' expectations and beliefs, which also depend heavily on race[1]. More than just changing perceptions and beliefs of students, same-race teachers can also increase students' short-term, course-level outcomes like test scores, grades, and behavior[2]. Because race matching has been shown to significantly impact short-term outcomes, it is plausible that it can also impact longer-term outcomes as the short-term effects build on each other. I examine short-term, course-level outcomes like pass rates and test scores in that course as well as longer-term, individual-level outcomes that are realized years after a race match like high school graduation and college enrollment.

An inherent issue in the student teacher demographic matching literature is that students and teachers are not randomly assigned to each other[3]. Much of the literature focuses on elementary and middle school students because as students get older, they have a greater choice in their courses, increasing the risk of endogenous teacher selection (Paufler and Amrein-Beardsley, 2014). High school race matching has been mostly unexamined because of the concerns of endogenous sorting despite high school's importance in determining college attendance and major choice.

To address this endogeneity concern, I exploit institutional details of the assignment of

[1]Ferguson (2003); Fox (2015); Papageorge, Gershenson and Kang (2018)

[2](Dee (2004); Dee (2005); Fairlie, Hoffmann and Oreopoulos (2014); Egalite, Kisida and Winters (2015); Holt and Gershenson (2017); Lusher, Campbell and Carrell (2018))

[3]Clotfelter, Ladd and Vigdor (2006); Rivkin, Hanushek and Kain (2005); Paufler and Amrein-Beardsley (2014);Rothstein (2009); Koedel and Betts (2011)

students to teachers in Texas. High school students in Texas have choices over courses, but they lack the choice of teacher conditional on courses. In order to minimize non-random sorting of students and teachers, I compare observationally similar students in the same high school that selected the same courses but were assigned teachers of different races. My strategy reduces observable same-race sorting by about 99% for each race. To address concerns of remaining observable and unobservable endogenous sorting, I implement the bounding methodology proposed by Oster (2019) and show that the results for minority students are largely robust to the potential issue of selection on unobservable characteristics and omitted variable bias.

I contribute to the literature in three main ways. First, I present the first research examining the effect of race matches in high school on college outcomes such as enrollment and major choice. These long-term effects of race matching on high school graduation and college enrollment have gone unexamined with the exception of Gershenson et al. (2018), which examines the effect of race matching for Black and White elementary students. They omit Hispanic and Asian students from their analysis, but Hispanic and Asian students grow every year as a percentage of the population, highlighting the importance of their inclusion in any analysis. My second contribution is that I include Hispanic and Asian students in my analysis, presenting the first evidence on the effect of race matching at any school level for Hispanic and Asian students on longer-term outcomes such as high school graduation and college enrollment. Finally, I add to the literature by providing additional estimates of the short-term effect of matching with a same-race teacher on test scores and pass rates using a large, detailed administrative dataset.

First, I examine the effect of matching with a same-race teacher in a course on course-level outcomes. Conditional on student and teacher fixed effects, I show that Black and Asian students perform significantly better on standardized test scores and pass rates in the class that they are matched with a same-race teacher. These students score better along both objective and subjective measurements of course performance with a same-race teacher, suggesting an increase in learning. I find no significant effect for short-term race matching effects for White or Hispanic students.

Next, I examine the longer-term effects of matching with a same-race teacher. I aggregate a student's 9th grade teachers and examine the effect of having an additional same-race teacher on the likelihood of graduating from high school and enrolling in college. To minimize non-random sorting, I compare students that selected the exact same set of courses but received teachers of different races. I find large effects from race matching for minority students in high school graduation and college enrollment. Hispanic and Asian students become significantly more likely to graduate high school with an additional same-race teacher. One additional race match for Black and Hispanic students significantly increases their likelihood of enrolling in college by 1 p.p. and 1.5 p.p., respectively. I find small effects for race matching for White students on two-year college enrollment, but I show that these results are not robust to the bounding methodology described in Oster (2019).

On top of college enrollment, I also explore how race matching within a subject affects college major choice as a freshman. One particular concern is that Black and Hispanic students in college are less likely to major in Science, Technology, Engineering, and Math (STEM) fields, which have larger wage premiums (Altonji, Blom and Meghir, 2012). I show that race matching has strong effects for major choice. One additional same-race STEM teacher in high school for Black and Hispanic students increases a student's likelihood of majoring in STEM as a college freshman by 0.7 p.p. and 0.6 p.p., respectively. An additional Hispanic teacher in social sciences for a Hispanic student increases their likelihood of majoring in social sciences by 0.3 p.p.

The previous results assume linearity. I relax this assumption and explore potential non-linear effects of race matching on these longer-term, individual level outcomes. The effect of race matching for Black and Hispanic students plateaus for certain outcomes like two-year college enrollment, suggesting that the effect of race matching could be non-linear. In the non-linear model, White students do not significantly benefit from any race matches in any outcomes, giving further evidence that these race-match effects are strongest for minority students.

Overall, I do not find robust, significant effects for White students benefiting from having same-race teachers on short-term, course-level outcomes like test scores nor on longer-term, individual-level outcomes like college enrollment. White students are greatly overrepresented in the teaching population. White teachers make up over 70% of high school teachers in Texas while White students only make up about 35% of the student population. My research suggests that policies to make the teaching population more representative would likely benefit minority students with minimal negative trade-offs impacting the White student population from having fewer same-race teachers.

2 Literature Review

Examining the effect of student-teacher demographic matching is not new. However, there is a dearth of literature examining high school race matching. An inherent issue in the student teacher matching literature is that students and teachers are not randomly assigned to each other, except in special cases like the STAR classroom experiment in Tennessee or in the military[4]. Typically, researchers believe that this non-random sorting of students and teachers increases with student age from elementary school to middle school to high school as students have greater choices in courses (Paufler and Amrein-Beardsley, 2014). Hence, researchers focus their attention on elementary and middle school where endogenous sorting is less likely to occur, leaving high school race matching woefully underexamined despite being an important time in a student's educational career.

I contribute to the literature by presenting the first evidence examining the effect of high school race matching on college outcomes. Sass (2015) is the only other paper to examine how high school race matching affects college outcomes, but he only examines indirect matching, using high school faculty composition and cannot directly observe matching within a

[4](Dee (2005); Carrell, Page and West (2010); Gershenson et al. (2018))

classroom. I improve on his paper by observing the exact match of students and teachers within a section in a course and not just the composition of teachers. Teacher composition may impact students not just through matching in the classroom but also through extracurricular activities like sports and clubs as well as having potential spillovers to affecting other teachers through peer effects. Estimating the effect of race matching using the faculty composition will provide a muddied estimate of the true effect of matching in a classroom. Sass (2015) also fails to account for high school fixed effects. I will show in my setting that high school fixed effects are critical for reducing endogenous same-race sorting and that one can reduce endogenous same-race sorting even more by including course information.

This research fits in with a few different literatures in the education field. It most closely relates to the student-teacher demographic matching literature. I will draw a distinction in the types of outcomes examined in the literature between short-term and longer-term outcomes. Short-term outcomes are outcomes that change in the classroom when a student and teacher match with each other like grades, behavior, expectations, and test scores. Long-term outcomes are outcomes that are realized years after a race match like college enrollment or graduation.

Much of the early research shows there are short-term benefits to race matching[5]. Much of the literature on sex matching complements this work and suggests similar effects for sex matching[6]. The literature suggests positive effects overall from demographic matching, but there is a notable hole in the literature on short-term benefits. These studies typically focus exclusively on White and Black students with only one other study examining course outcomes from race matching for Hispanic and Asian students (Egalite, Kisida and Winters, 2015). I contribute to the literature by providing the only other estimates of short-term benefits from race matching for Hispanic and Asian students as well as providing additional estimates for White and Black students using a large administrative dataset.

[5](Dee (2004); Dee (2005); Fairlie, Hoffmann and Oreopoulos (2014); Egalite, Kisida and Winters (2015); Holt and Gershenson (2017); Lusher, Campbell and Carrell (2018))

[6](Nixon and Robinson (1999); Dee (2006), Dee (2007); Cho (2012); Winters et al. (2013); Sansone (2017))

A major short-coming of the student-teacher race matching literature is the focus on short-term outcomes. I present the first paper to examine long-term effects of race matching for Hispanic and Asian students. Only one paper tackles the question of long-term effects by looking at the Tennessee STAR randomization experiment (Gershenson et al., 2018). They show that Black students that were randomly assigned a Black teacher in Kindergarten to third grade are 5 p.p. more likely to graduate high school and 4 p.p. more likely to enroll in college. However, they fail to address how race matching affects Hispanic and Asian students, which I examine. Many of the race matching studies focus exclusively on Black and White students for sample size purposes [7]. However, Hispanic students are nearly 50% of public high school students in Texas. The Hispanic and Asian population are large and growing groups in the United States, underlying the importance of their inclusion.

Gershenson et al. (2018) examines the long-term effects of race-matching for Black and White students in elementary school on high school graduation and college enrollment. My paper furthers the literature by analyzing the timing of race-matching and its importance. Heckman emphasizes the need for interventions to occur as early in a childhood as possible, showing that effects impacting skills and learning grow and build over time in a synergistic fashion (Heckman (2000); Cunha and Heckman (2007)). Race-matching in elementary school has large effects on high school graduation and college enrollment (Gershenson et al., 2018). Whether or not this effect is still present from race-matching in high school is an open question and informs this broader literature on the timing of educational interventions. Students exposed to same-race teachers in high school may not have sufficient time to change their skills and human capital from the treatment relative to students in elementary school. Students in high school may also have stickier beliefs about returns to education, suggesting an attenuated effect relative to an elementary school match. I confirm this hypothesis in the results section, showing that the effect of Black students matching in high school on college enrollment is about 25% smaller than what Gershenson et al. (2018) finds for matching in

[7] (Dee (2004); Dee (2004); Gershenson et al. (2018))

elementary school.

There are several potential reasons why demographic matching of students and teachers may improve student outcomes. One theory of race matching impacting student outcomes is that same race teachers have a culturally relevant pedagogy (Ladson-Billings, 1995). Students benefit from same-race teachers because those teachers can effectively communicate in a cultural context by helping students affirm their cultural identity and challenge inequities that schools can instill and perpetuate (Ladson-Billings, 1995). Related to culturally relevant pedagogy, cultural synchronization describes the interpersonal cultural context that exist between Black students and teachers (Irvine, 1990). This cultural relevancy of same-race teachers has also been documented qualitatively in Native Hawaiian children and native American students in observing student-teacher interactions (Au and Jordan (1981); Mohatt, Erickson et al. (1981)).

Another potential reason is that underrepresented students interacting with a same-race teacher may benefit from a role model effect, updating their beliefs about returns to education and increasing their learning (Walker (2001); Marx and Roman (2002); Dee (2005)). A growing literature on students' and teachers' beliefs and expectations suggest that race-matching can greatly improve a student's expectations about their own abilities, an important input to education (Dee (2005), Fox (2015); Papageorge, Gershenson and Kang (2018)).

This research also informs the college major choice literature. Much of the major choice literature focuses on college interventions like faculty composition or peer groups [8]. Some of this literature focuses on the persistence of students in a STEM major, but it misses a crucial determinant of major preference – high school. Most of the work on high school factors impacting major choice in college are descriptive but suggest that high school is where many students form their preferences for subjects and subsequently their future major in college [9]. The best paper on high school determinants of college major choice instrumented

[8](Canes and Rosen (1995); Bettinger and Long (2004); Ost (2010); Price (2010); Fischer (2017))

[9](Maltese and Tai (2011); Rask (2010); Morgan, Gelbgiser and Weeden (2013); Bottia et al. (2015); Bottia et al. (2018))

for additional math and science course taken with state law changes and show a significant increase in STEM majors (Federman, 2007).

I contribute to the literature in three main ways. First, I am the first to examine direct high school race matches on college outcomes such as enrollment and college major choice. Second, I am also the first to examine long-term effects for race matching for Hispanic and Asian students. Finally, I add to the literature by providing additional estimates of the short-term effect of matching with a same-race teacher on test scores and pass rates using a large, detailed administrative dataset. Texas, the setting of my research, is an incredibly large and diverse state with many Hispanic, Black, Asian, and White students allowing me to take a robust snapshot of race matching in high school.

3 Data

My data come from the Texas Education Research Center, combining data from the Texas Education Agency (TEA), the Texas Higher Education Coordinating Board (THECB), and National Student Clearinghouse (NSC). The TEA, the regulatory body that oversees K-12 education in Texas, collects data on student enrollment, demographics, and outcomes on the universe of students in public K-12 education. The THECB is the higher education counterpart to TEA. The THECB only collects information on students in higher education in Texas, so I supplement that data with NSC data, which contains enrollment and major choice for all colleges in the United States. The datasets are linked using de-identified Social Security numbers, ensuring high-quality links between high school and college outcomes.

I observe every section that a student is assigned to in every course that student takes. I also observe every student and every teacher in every public high school from 2012 to 2016. The data differentiate between Advanced Placement and International Baccalaureate courses and regular courses as well as advanced and remedial courses, allowing me to control for different tracking of students. I follow the 2012 and 2013 freshmen cohorts for four years in high school and one year afterwards to examine college enrollment and major choice. I limit my course sample to sections without co-teachers that have section sizes larger than or equal to five and less than or equal to 40. Sections smaller than 5 are typically special classes with selected students. Most sections larger than 40 are mainly large physical education courses. Finally, I eliminate all music, art, physical education, and foreign language courses to focus on academic courses.

Starting in 2012, TEA began collecting class-level data on which teachers were assigned to which student in a given course and whether a student passed that course or not. I link the course level information to student test scores, which TEA administers in five courses: Algebra I, Biology, English I, English II, and US History. I normalize the test scores to a Z-score with a mean of zero and standard deviation of one. The TEA administers these standardized tests to all students that take these courses in the state, and the students must pass these tests to receive credit for the courses. These standardized tests are high-stakes, multiple choice tests with little to no room for subjective grading. These are the only five standardized tests that are administered to students in high school in Texas, so I can only examine the effect of race matching on a student's test scores in these five courses. Another outcome I examine is whether the student passed their course, which I observe in every course. These two related yet distinct measures of course performance allows for testing of different mechanisms. The state of Texas grades test scores objectively through multiple choice grading, while teachers determine if a student passes a class through some combination of grading of assignments and interactions in the class.

My outcomes separate into two different categories: short-term, course-level outcomes, and long-term, individual-level outcomes. The short-term, course-level outcomes such as test Z-scores and an indicator for passing a course vary at the course level where I can see a student have multiple outcomes. I examine the effect of race matching in a course on these outcomes which are vary at the course-level. The long-term outcomes such as high school graduation, college enrollment, and major choice are individual-level outcomes that are constant for a given individual. I estimate the effect of race matching at the individual-level after a student matches with a 9th grade teacher of the same race. I define high school graduation as graduating four years from 9th grade and enrollment in college as enrolling five years from 9th grade. I observe what major students choose as a freshman in college and if they attend a two- or four-year college. I examine all academic courses that every student in public high school takes and the teacher that they are assigned, resulting in about 9 million student-course observations for 649,320 students and 78,453 teachers.

TEA data also contains detailed demographic information on students including race, age, sex, free or reduced-price lunch status and indicators for if a student is considered gifted or at-risk of dropping out. I also include 8th grade test scores taken by students to control for pre-high school ability in school. The data contains detailed demographic information on teachers as well as students, including race, sex, education level, pay, tenure, experience, and age. I use the detailed demographics of students and teachers to determine race matches and control for potentially confounding factors.

I present some descriptive statistics on differences in academic outcomes and characteristics by race in Table 1 where the unit of analysis is the student in Panel A. Unsurprisingly, large gaps exist in academic achievement along racial lines. Black and Hispanic students are far less likely to graduate high school, enroll in college, and major in STEM compared to their Asian and White counterparts. They are also less likely to pass their courses and on average have lower standardized test scores. Asian students have the highest rates of academic achievement with respect to high school graduation, college enrollment, test scores, and pass rates. Students also show extreme disparities in student characteristics along race lines that may be a function of a lack of representation in teachers at a younger age in elementary school. For instance, Black and Hispanic students are far less likely to be considered "gifted and talented" than White or Asian students.

In Panel B of Table 1 I show the statewide racial composition of students and teachers. The teacher composition in high school is overwhelmingly White relative to the student population. White students make up 33% of the student population but over 70% of the teachers in the sample are White. Black and Hispanic teachers comprise only about 9% and 18% of the sample, respectively. Black, Hispanic, and Asian students are underrepresented in the teacher composition relative to White teachers who comprise the vast majority of teachers.

4 Methodology and Empirical Strategy: Short-term

4.1 Sorting

An inherent issue in the student-teacher matching literature is that schools do not randomly assign students to teachers. Unfortunately for the econometrician, students have choices over what courses to take and subsequently what teachers they are assigned. Researchers commonly believe that the non-random sorting of students and teachers increases as students' age increases from elementary to middle school and middle school to high school as students get older and are given greater freedom in which courses they can take (Paufler and Amrein-Beardsley, 2014). This belief about sorting helps explain why much of the student-teacher matching literature focuses on elementary and middle school students with a dearth of studies on high school matching.

Sorting, especially along race lines, is most prominent across high schools with large amounts of racial segregation across schools. However, sorting also occurs within schools as well (Clotfelter, Ladd and Vigdor (2006); Rivkin, Hanushek and Kain (2005); Paufler and Amrein-Beardsley (2014);Rothstein (2009); Koedel and Betts (2011)). The pre-college literature on matching in observational studies focuses on using student fixed effects (Dee (2007); Winters et al. (2013); Sansone (2017)), but researchers admit that student fixed effects are likely not sufficient to solve sorting as an issue (Dee, 2005).

Another attempt to get around non-random sorting is to use variation in teacher composition in college faculty to instrument for a match by sex (Bettinger and Long, 2004). The technique has been applied in matching papers for race in elementary school (Gershenson et al., 2018). One potential issue is that these papers do not identify the effect of a match but instead are identifying off of a general composition change, and the effect could be working through other mechanisms such as extracurricular activities with student clubs and athletics (Gershenson et al., 2018).

Conversations with Texas high school administrators suggest that students have choices over the courses they take, but they have no choice in which teacher they are assigned conditional on course selection. The precise mechanism for assigning students and teachers to classroom likely varies across school districts and schools and is unobservable. The natural experiment that I will exploit is by comparing two students in a given high school that both take the same course in same academic year, but one student is assigned teacher A and the other is assigned teacher B. For example, two Black students in the same high school choose to both take Algebra 1 in 2013, but one student is assigned to Black teacher and the other is assigned to a White teacher. To implement this, I employ a high school-by-year-by-course fixed effect.

My identifying variation in this case will be courses in a given high school and year that have multiple teachers with different races such that one teacher would produce a race match for a student and the other teacher would not. I present the high school campuses with courses that have multiple teachers with different races in Figure 1, showing the relationship between students and teachers of the same race. The gray points in the scatter plot show which schools lack multiple different race teachers for any courses. The identifying variation comes from the courses at the high schools with color. The figure shows a strong clear correlation between the student and teacher composition at the school level, stressing the need to examine within a high school. It also shows that the campuses that are heavily composed of one race for teachers do not contribute to the identifying variation since they lack multiple race teachers at the course level. The figure shows that there are several points close to each other but some campuses have courses contributing to the identifying variation and others do not. Campuses with similar student and faculty composition can also vary in whether they have courses with multiple teachers of different races.

One way to test my fixed effect strategy is to examine how likely a student of a given race/ethnicity is to be assigned a teacher of the same race/ethnicity and how that likelihood changes as I introduce additional information. In an ideal scenario, one would randomize students to teachers, and students would be no more likely to receive a same-race teacher than a student of a different race. For example, a Black student would ideally be no more likely than a White student to have a Black teacher. To test how similar the student to teach assignment is to the ideal experiment, I run the following regressions with varying fixed effects to see how sorting changes where the unit of analysis at the student by course level.

$$BlackTeach_{jc} = \alpha_1 BlackStu_{ic} + \alpha_2 X_{it} + \phi_{hct} + \epsilon_{ijhct} \tag{1}$$

$$HispTeach_{jc} = \beta_1 HispStu_{ic} + \beta_2 X_{it} + \phi_{hct} + \epsilon_{ijhct} \tag{2}$$

$$AsianTeach_{jc} = \gamma_1 AsianStu_{ic} + \gamma_2 X_{it} + \phi_{hct} + \epsilon_{ijhct} \tag{3}$$

$$WhiteTeach_{jc} = \delta_1 WhiteStu_{ic} + \delta_2 X_{it} + \phi_{hct} + \epsilon_{ijhct} \tag{4}$$

In these equations, I regress an indicator for student i's race in course c on an indicator for teacher j's race. I include a vector of student characteristics including demographic and socio-economic factors such as free and reduced priced lunch status, gifted and talented status, and 8th grade test scores to control for pre-high school ability in school. Finally, I include ψ_{hct} giving high school by year by course fixed effects. The coefficients of interest are α_1, β_1, γ_1, and δ_1. In equation (1), α_1 represents the likelihood that a Black student will have a Black teacher relative to a White student as White students are used as the reference group. β_1 and γ_1 represent the likelihood a Hispanic or Asian student will have a same-race teacher relative to a White student. Finally, δ_1 represents the likelihood that a White student will have a White teacher relative to a Hispanic student.

In Figure 2, I show how α_1, β_1, γ_1, and δ_1 vary, becoming closer to zero when changing from no fixed effect to high school fixed effect to high school-by-year-by-course fixed effects. I cluster my standard errors at the school level. I present the full output in regression tables in the Appendix Tables A1-A4. We can see that in the regression without fixed effects, Hispanic students are about 22 p.p. more likely to have a Hispanic teacher relative to a White student. However, when using the high school by year by course fixed effects, this non-random sorting is greatly reduced to Hispanic students being 0.12 p.p. more likely to have a Hispanic teacher, a more than 99% reduction in the likelihood. While Hispanic students are statistically significantly more likely to have a Hispanic teacher, the increased likelihood is economically small. The increased likelihood suggests that for every 820 courses that Hispanic students take, there is one additional Hispanic teacher than there would be under true random assignment.

Another way to empirically test how sorting changes is to examine which covariates of students predict having a same race teacher and how those covariates change with additional fixed effects. In an ideal experiment with randomization, Hispanic students receiving free or reduced priced lunch would be no more likely to receive a Hispanic teacher than Hispanic students paying full price for lunch. I limit each regression to one race of students and see which covariates predict same race teachers. Specifically, I run the below regressions, limiting each regression to only one race to examine what covariates of Black students predict having a Black teacher or what covariates of Hispanic students predict having a Hispanic teacher.

$$BlackTeach_{jc} = \alpha_3 X_{it} + \phi_{hct} + \epsilon_{ijhct} \tag{5}$$

$$\text{if } StuBlack_{ic} = 1$$

$$HispTeach_{jc} = \beta_3 X_{it} + \phi_{hct} + \epsilon_{ijhct} \tag{6}$$

$$\text{if } StuHisp_{ic} = 1$$

$$AsianTeach_{jc} = \gamma_3 X_{it} + \phi_{hct} + \epsilon_{ijhct} \tag{7}$$

$$\text{if } StuAsian_{ic} = 1$$

$$WhiteTeach_{jc} = \delta_3 X_{it} + \phi_{hct} + \epsilon_{ijhct} \tag{8}$$

$$\text{if } StuWhite_{ic} = 1$$

The coefficient α_3, represents the likelihood that a Black student with a given characteristic will have a black teacher, and β_3 represents the likelihood that a Hispanic student with a given characteristic will have a Hispanic teacher. I cluster my standard errors at the school level. I present these coefficients and how they change in response to different levels of fixed effects in Figure 3. The corresponding regression tables are displayed in Appendix Tables A5-A8.

A consistent pattern of convergence to zero seen in the two sorting methodologies suggests that including high school fixed effects better controls for non-random sorting than the regressions without fixed effects, as seen in Sass (2015). Including the course information by including the high school by year by course fixed effects also reduces the non-random sorting further than the high school fixed effects as well.

4.2 Estimation

I examine two different types of outcomes: course-level outcomes and individual-level outcomes. The course-level outcomes such as test Z-score and pass rates vary at the course for each individual. This variation allows me to estimate the effect of race matching with the inclusion of student-level fixed effects to control for time-invariant student characteristics. Including student fixed effects is another strategy that previous researchers have used to control for non-random, endogenous sorting of students and teachers.[10] I also include the high school by year by course fixed effect to minimize sorting. For the course-level outcomes, I estimate the effect of race matches using this strategy below where the unit analysis at the student by course level:

$$\begin{aligned} Z_{ijct} = {} & \beta_1 BlackMatch_{ijc} + \beta_2 HispMatch_{ijc} + \beta_3 AsianMatch_{ijc} + \beta_4 WhiteMatch_{ijc} \\ & + \gamma_1 X_{it} + \gamma_2 \pi_{jt} + \psi_i + \delta_j + \phi_{hct} + \epsilon_{ijhct} \end{aligned} \tag{9}$$

Here Z_{ijct} gives the Z-score for a standardized test for student i with teacher j in course c in year t. Another outcome examined is an indicator for if the student passes her course. Each match variable is an indicator for if the student matches along race lines with her teacher in course c. There is a vector for time-varying student characteristics in X_{it} and for time-varying teacher characteristics in π_{jt}. Finally, I include three fixed effects: student fixed effects, ψ_i, which controls time-invariant unobservable student characteristics; teacher fixed effects, δ_j, to control for time-invariant teacher characteristics like quality; and high school by year by course fixed effects, to control for non-random sorting of students and teachers across courses. I cluster my standard errors at the school level.

The coefficients of interests are β_1, β_2, β_3, and β_4 and the interpretation on the coefficients is the effect of having a race match for Black, Hispanic, Asian, and White students, respectively. These coefficients estimate the effect of a race match relative to another student of that same race who received a different race-teacher. For instance, β_1 gives the effect for a Black student having a Black teacher relative to a Black student having a non-Black teacher conditional on student and teacher fixed effects.

This estimation strategy is akin to a difference-in-difference with the high school by year by course and student fixed effects. The student fixed effects make the regression estimates

[10] Dee (2007); Winters et al. (2013); Sansone (2017)

the change in a student's test scores with a same-race teacher relative to that student's test scores with a different-race teacher. The high school by year by course fixed effect will compare students with a race match to students without a race match taking the same course. The result of having both in the equation is that β_1, β_2, β_3, and β_4 are estimating the change in a student's test scores with a race match to the change in a student's test score without a race match.

For example, without the student fixed effect, β_1 would compare the test score of a Black student with a Black teacher to the test score of a Black student with a non-Black teacher, which is one difference. Adding in the student fixed effect will make the comparison within the student as well, adding another difference. Using both student and high school by year by course fixed effect creates two differences that contribute to the coefficients of interest. This estimation strategy is not a traditional difference-in-difference estimation, but it is a similar strategy by comparing the difference between the change in test scores for students with and without a same-race teacher.

5 Short-term Results

5.1 Course-level Outcomes

In Table 2, I present the course-level outcomes and the effect of a race match. When examining the short-term outcomes from the course that a student matches with same-race teacher, Black and Asian students perform significantly better. Black students matched with Black teachers perform 0.013 standard deviations better on standardized tests and are 0.9 p.p. more likely to pass their courses than they would have if they had a non-Black teacher. Asian students have a larger premium from race matching with an increase of 0.07 standard deviations on standardized tests and become 1.4 p.p. more likely to pass their courses. Test scores are limited to only five courses: Algebra I, Biology, English I, English II, and U.S. History, so the sample size is smaller than that of the regression looking at the course pass rate.

Ultimately, test scores and pass rates are two different measures of a student's performance in a course. However, they vary in how they are graded. Texas administers the tests to all students in the state that take Algebra I, Biology, English I, English II, or U.S. History. The tests are graded externally and are multiple choice, eliminating subjective grading. The English exams have essays, which are also graded by the state with a systematic rubric. Students must pass these high-stakes tests to earn credit for the courses, each of which is a mandated class to graduate high school. On the other hand, passing a class is dependent on the student-teacher interactions with a teacher's discretion playing a role at multiple points. Whether or not a student passes a class is more a subjective measure than the student's performance on a standardized, state-wide exam. One concern would be if students became more likely to pass their classes but did not improve their test scores, which could indicate that teachers are more favorable with their grading to same-race students. However, given that there are significant improvements in test scores and pass rates, the findings suggest that Black and Asian students perform better with same-race teachers in objective and subjective measures of performance.

Interestingly, only Black and Asian benefit from race matching in the short-term. Hispanic and White students do not significantly improve their test scores or pass rates. To assess reasons for why there may be an effect for Black and Asian students, we should assess the mechanisms for an improved performance with a same-race teacher. There are two main theories behind why students perform better with same race teacher. The first is that teachers more effectively communicate ideas and teach same-race students because there is some shared cultural connection (Irvine (1990); Ladson-Billings (1995)). The second is that teachers act as role models to students, updating their beliefs about own abilities or returns to education, and these role models may be more effective for students who are more underrepresented (Marx and Roman (2002); Dee (2005)).

One potential explanation for this split in race-match results is that Black and Asian teachers and students are relatively rare compared to White and Hispanic teachers and students in Texas. As I show in Table 1, Black and Asian teachers make up 9% and 2% of the teacher population, and Black and Asian students make up a small fraction of the student body in Texas high schools at 14% and 4%, respectively. Making up a smaller proportion of the student body may make race-matching more salient for Black and Asian students. In particular, it may mean that the culturally relevant interactions for Black and Asian students that are matched with a same-race teacher are more poignant and more effective, whereas Hispanic and White students are effectively a majority already at 50% and 33% of the student population, respectively. However, these culturally relevant interactions for Black and Asian students do not necessarily preclude role model effects from occurring either as both of these mechanisms could be working together. Later on, I will test whether or not role model effects are a potential mechanism for long-run outcomes using a model developed by Gershenson et al. (2018).

5.2 Heterogeneity

One potential source of heterogeneity is in student ability. It is possible that the gains from student-teacher race matching are stronger for students at the bottom of the distribution. Given that Black and Asian students are more likely to pass their classes when they have a same-race teacher would suggest that students at the bottom of the distribution are affected because a student going from a "C" to an "A" would not be captured by the passing measure, but a student going from a "F" to a "C" would be captured in this measure.

To explore how matching affects students of different ability, I break down the sample into quartiles by 8th grade standardized test scores in reading and re-run the analysis. Given the tests were taken in 8th grade, they will be unaffected by any intervention at the high school level and should work as an approximation for a student's underlying ability in school. I present the course-level outcomes in Table 3:

The pattern seen in the average effects is mostly the same with Black and Asian students benefiting from matching via race lines with one exception. Hispanic students at the bottom of the test score distribution become 0.3 p.p. more likely to pass their classes with a Hispanic teacher. For Black students, the effect of race matching on test scores and pass rates is negatively correlated with 8th grade reading scores. There is also a negative correlation in the effect size of race matching on tests score, but no correlation for the effect on passing a course.

The correlations between 8th grade reading scores and the effect of race-matching on improving test scores suggest that Black and Asian students at the lower-end of the ability distribution are most impacted by having a same-race teacher. It is possible that the lower-ability students can make up more ground from a race-match relative to their higher-ability peers. There's a different interpretation for the effect on pass rates though. The declining effect may not be a function of decreased effectiveness of a match. A student at the higher end of the ability distribution may also benefit from matching but the passing rate may not be the margin that is impacted. A high-ability student may go from earning a "B" in a class to earning an "A" from race matching with a teacher, but that would not impact their pass rate. However, high-ability Black and Asian students still have their pass rate significantly improved from race matching, even though these students were already more likely to pass their classes than their lower-ability peers.

6 Methodology and Empirical Strategy: Long-term

6.1 Sorting

In the short-term empirical strategy, my previous unit of analysis is at the student by course level, which naturally fit with course-level outcomes like test scores and pass rates. However, for longer-term, individual-level outcomes like high school graduation, college enrollment, and major choice that vary at the individual level the unit of analysis should be at the student level. My identification strategy for course-level outcomes comes from variation at the course-level with respect to which teachers are assigned to which students and uses a high school by year by course fixed effect. Aggregating the data to the student-level will lose this granular course information. I implement a course-set fixed effect to circumvent this aggregation problem. The course-set fixed effect will group together and compare student who took the exact same set of academic courses in the 9th grade in a given high school, allowing the aggregated student-level outcomes to retain course information.

This course-set fixed effect effectively exploits the same variation as the high school-by-year-by-course fixed effect while also controlling for the other courses that a student also took. I compare students in the same high school with identical course selections, but one student idiosyncratically receives more same-race teachers than a different student. For example, two Black freshmen students at the same high school both selected to take Algebra 1, English 1, Chemistry, and Geography, but one of these students received a Black Algebra 1 teacher and the other received a White Algebra 1 teacher. My strategy will compare these two students because they have the same course-set but different teachers conditional on their course selection.

My sample selection changes slightly as there are some students without a comparable student with an identical course-set in a given high school, but my sample is still left with over 500,000 students over two cohorts. I present summary statistics in Table 4, which suggest that the new sample is slightly negatively selected with respect to high school graduation as compared to the previous sample with all students in it. However, the racial composition of students and teachers looks nearly identical to the sample in the first section examining short-term outcomes. The new sample is similar in enrollment to the old sample as well.

I create the course-set using the 9th grade courses that a student selects and the teachers they are as. I focus on 9th grade courses because down-stream race matches in later grades are potentially endogenous. Race matching in the 9th grade potentially affects a student's propensity to remain in high school. Later race matches in the 10th, 11th, and 12th grade are a function of race matching in the 9th grade and are endogenous if 9th grade race matches increase a student's likelihood to persist in school. However, I do show in the robustness check section that including 10th grade courses does not meaningfully change the estimates.

I run similar sorting estimation strategies as the previous section to see how well this specification controls for endogenous sorting. Similar to the previous sorting strategies, I present the regression output with varying levels of fixed effects to examine how non-random sorting changes and gets closer to zero using the full course-set fixed effects. Specifically, I estimate the below equations:

$$NumBlackTeach_i = \alpha_1 BlackStu_i + \alpha_2 X_i + \kappa_s + \epsilon_{is} \tag{10}$$

$$NumHispTeach_i = \beta_1 HispStu_i + \beta_2 X_i + \kappa_s + \epsilon_{is} \tag{11}$$

$$NumAsianTeach_i = \gamma_1 AsianStu_i + \gamma_2 X_i + \kappa_s + \epsilon_{is} \tag{12}$$

$$NumWhiteTeach_i = \delta_1 WhiteStu_i + \delta_2 X_i + \kappa_s + \epsilon_{is} \tag{13}$$

In these equations, I regress the number of same-race teachers that a student has in 9th grade on an indicator for a student's race on. X_i is a vector of student characteristics including gifted/talented status, free/reduced price lunch status, and 8th grade test scores. κ_s is the course-set fixed effect. I also include a specification with a cohort course-set fixed effect to limit the course-set comparisons to within a cohort. The standard errors are clustered at the school level. Similar to the previous sorting equations, I present these coefficients graphically in Figure 4. The corresponding regression tables are displayed in Appendix Tables A9-A12.

I run the covariate sorting equations from the previous section as well to examine which covariates predict having more same-race teachers and how those covariates change with the course-set fixed effect. I run the regressions below, limiting each regression to only one race of students to examine which covariates of students predict having more same-race teachers. The standard errors are clustered at the school level.

$$NumBlackTeach_i = \alpha_3 X_i + \kappa_s + \epsilon_{is} \tag{14}$$
$$\text{if } StuBlack_i = 1$$

$$NumHispTeach_i = \beta_3 X_i + \kappa_s + \epsilon_{is} \tag{15}$$
$$\text{if } StuHisp_i = 1$$

$$NumAsianTeach_i = \gamma_3 X_i + \kappa_s + \epsilon_{is} \tag{16}$$
$$\text{if } StuAsian_i = 1$$

$$NumWhiteTeach_i = \delta_3 X_i + \kappa_s + \epsilon_{is} \tag{17}$$
$$\text{if } StuWhite_i = 1$$

I present coefficients $\alpha_3, \beta_3, \gamma_3$, and δ_3 in Figure 5. The corresponding regression tables are displayed in Appendix Tables A13-A16. In an ideal randomized experiment, these covariates would be balanced. For example, a gifted Black student would ideally be no more or no less likely to have more Black teachers than a non-gifted Black student. These regressions allow one to examine how the balance of covariates changes with different fixed effect strategies.

Overall, in both Figures 4 and 5 that there is a general convergence of the coefficients that indicate non-random sorting toward zero, suggesting that there is a reduction in the non-random sorting of students to same-race teachers. In particular, nearly all of the covariates that predict having a same-race teacher converge to zero and are no longer statistically significant, bringing this natural experiment closer to a plausibly random distribution. The figures suggest course-set fixed effects strongly reduce the amount of endogenous sorting that occurs over no fixed effects or high school fixed effects.

6.2 Estimation

I use the course-set fixed effects to estimate the effect of matching with a same race teacher in high school in a linear dosage model. I estimate the following regression:

$$\begin{aligned} Y_i = {} & \beta_1 BlackMatch_i + \beta_2 HispMatch_i + \beta_3 AsianMatch_i + \beta_4 WhiteMatch_i \\ & + \gamma_1 X_i + \kappa_s + \epsilon_{is} \end{aligned} \tag{18}$$

In this regression, Y_i is an indicator for if student i graduated from high school within four years of 9th grade or enrolled within five years of 9th grade. X_i is a vector of student level characteristics, and κ_s is the course-set fixed effect, grouping students in the same high school who took identical courses. Each of the match coefficients are identified from students of the same-race having different teacher compositions conditional on their selected courses. The reference group for these match terms is in relation to a non-match, allowing for an easy to interpret coefficient. The match variables are in counts for the linear dosage model, so β_1, β_2, β_3, and β_4 represent one additional race match in the 9th grade for Black, Hispanic, Asian, and White students, respectively. I do not include a high school fixed effect as it is implicitly nested within the course-set fixed effect. I include an additional specification with cohort-course-set fixed effects, limiting the comparison to students with identical course sets in the same 9th grade cohort.

The dosage model allows one to test marginal impact of same-race teachers. Whether or not there are increasing, constant, or diminishing marginal returns is of first order importance as it allows for researchers to develop concrete policy recommendations. For example, if there are increasing marginal returns to having same-race teachers, it could suggest evidence in favor of having as many same-race teachers as possible.

Another benefit to determining the marginal effects is that it gives testable implications for the mechanisms behind positive race match effects. Gershenson et al. (2018) develop a dosage model with testable implications for how race matching can impact students. One theory of race matching suggest that same-race teachers are more effective at communicating with students and expanding their worldview through culturally relevant pedagogy and cultural synchronization (Irvine (1990); Ladson-Billings (1995)). Another theory of race matching suggests that there is a role-model effect where teachers serve as role models to students, which could impact students by updating their inaccurate beliefs about returns to human capital. Minority students may have an inaccurate belief about being able to attend college despite having sufficient ability to do so and having a same-race teacher could update that belief.

The model developed by Gershenson et al. (2018) gives implications on how the marginal same-race teacher will impact educational outcomes with constant marginal returns to same-race teachers suggesting an increased effectiveness mechanism and diminishing marginal returns suggesting a role model effect. The intuition behind this implication is that increased effectiveness would be present no matter how many previous same-race teachers one had. On the other hand, role model effects work through changing a student's beliefs about themselves or the returns to education and that the 6th same-race teacher that a student had would presumably update their belief less than the 1st same-race teacher.

To test the non-linear effects of race-matching, I estimate a flexible dosage model, allowing for varying marginal effects. I create indicators for the number of same race teachers that a student could have. For Black, Hispanic, and White students the number of same-race teachers varies from zero to six, and for Asian students, it varies from zero to three. The reduction in potential matches for Asian students is lower simply because there are so few Asian students and teachers that there are no Asian students in the sample with more than three Asian teachers. Specifically, I estimate the below equation:

$$
\begin{aligned}
Y_i = &\sum_{k=1}^{k=6} \theta_k \mathbb{1}(BlackMatch_i{=}k) + \sum_{k=1}^{k=6} \lambda_k \mathbb{1}(HispMatch_i{=}k) \\
&+ \sum_{k=1}^{k=3} \nu_k \mathbb{1}(AsianMatch_i{=}k) + \sum_{k=1}^{k=6} \eta_k \mathbb{1}(WhiteMatch_i{=}k) \\
&+ \beta_1 X_i + \kappa_s + \epsilon_{is}
\end{aligned} \tag{19}
$$

The notation is the same as the previous regressions. However, the interpretation on coefficients on the match terms changed. The omitted category for these match terms is students with no race matches, so the interpretation on θ_2 is the effect of 2 race matches for a Black student relative to a Black student with 0 race matches.

7 Long-term Results

7.1 Individual Results

I present the linear results in Table 5 which shows the specifications with the course-set fixed effects and the cohort course-set fixed effects. The results for the course-set fixed effects and cohort course-set fixed effects are nearly identical. I present the coefficient for each race-match next to the race-specific mean for context to the size of the effect.

Black students become significantly more likely to enroll in college, driven by four-year college enrollment, after race matching in the 9th grade. One additional Black teacher for a Black student increases the likelihood of enrolling in a four-year college by 1 percentage point. Hispanic students benefit across all outcomes when race matching. Hispanic students matched with one additional Hispanic teacher increase their likelihood to graduate from high school by 0.7 p.p., likelihood to enroll in any college by 1.5 p.p., likelihood to enroll in a two-year college by 0.7 p.p., and likelihood to enroll in a four-year college by 0.9 p.p.

However, underrepresented minority students are not the only group to benefit from race matching in this linear model. Asian students become 1.8 p.p. more likely to graduate from high school following an additional race match in 9th grade. Although, the confidence interval is so much wider on the estimate for an Asian match than the other races. Finally, White students become 0.7 p.p. more likely to enroll in college, and 0.4 p.p. to enroll in a two-year college after one additional race match in 9th grade. However, I will show in the Robustness Check section that the results for White students in the linear dosage model are not robust to Oster (2019) and her bounding methodology. The results for White students are the only long-term results that are not robust, suggesting that White students may not benefit from race-matching.

One potential downside to this linear model is that it imposes an assumption of constant marginal effects for the effect of race matching. This is particularly troublesome as the racial distribution of teachers is so skewed toward White teachers. This skewed distribution is evident in the summary statistics with White students having 3.7 race matches on average, compared to the 0.9 race matches Black students have on average. Given how skewed these distributions are, it is plausible that the effect varies accordingly with the amount of matches a student receives, which could also vary by race.

The functional form of the effect over a different amount of race matches is also of first order importance for determining policy implications. Another benefit to determining the functional form is that it would allow one to test different mechanisms of how race-matching impacts educational outcomes using the model developed by (Gershenson et al., 2018). In their model, constant marginal returns suggest that students improve with same-race teachers because teachers are more effective at teaching same-race students, while diminishing marginal returns would suggest that role model effects are present.

To test how marginal effectiveness of same-race teachers varies, I do not impose any functional form on the effect of additional race-matches, allowing the marginal effect of race-matching to vary. I run regression (19) specified in the previous section creating indicators for each amount of race match for each race. I present the coefficients for the effect of race matching on high school graduation and college enrollment in Table 6, and I plot the coefficients in Figure 6. I present the coefficients for the effect of race matching on two- vs four-year enrollment Table 7 and in Figure 7. To show the context of the distribution of race matches by race, I plot a histogram overlaid on Figure 6 and Figure 7 to show the support for each coefficient estimated.

In Figure 6 and Figure 7, the confidence intervals can be fairly large since the sample used to estimate each coefficient is smaller than in the linear or quadratic models, and many of the estimates are statistically indistinguishable from each other. However, looking at the point estimates can still be instructive in terms of the estimated effect. For all of the enrollment outcomes, there does appear to be diminishing marginal returns when examining the point estimates. For Black students enrolling in any college or a four-year college, there is a linear increase in the effectiveness until about the third race match when there is a plateauing of an effect. For Hispanic students enrolling in any college or a two-year college, there is a diminishing increase with a small negative marginal effect from the sixth match. Four-year enrollment for Hispanic students looks to be monotonically increasing with Hispanic matches but still with diminishing marginal effects. The effect on high school graduation for Black and Hispanic students is seemingly different from the enrollment outcomes. For both of Black and Hispanic students, the effect of race matches on high school graduation appears to small or zero until getting five or six race matches, at which point the point estimates shoot up.

For Asian students, it can be difficult to assess the shape of the curve as the sample size gets increasing small when breaking the groups up further. Finally, for White students, there are clear diminishing marginal returns with no coefficient on the match terms being significantly different from zero for all outcomes. The non-linear results for White students seem to contradict the linear results where there were significant effects for White students in any college enrollment and two-year college enrollment. One potential way of reconciling this is by examining the distribution of matches for White students. About 75% of race matches for White students are between one and four where there is a clear positive relationship for these outcomes and race matches. However, for the fifth and 6th matches, the marginal effect becomes negative. This non-linear relationship between race matches and marginal effects underlies the importance of allowing the model to be flexible without imposing linearity.

In particular, the diminishing marginal returns in race matches and Gershenson et al. (2018) suggest that role model effects are present and are potentially acting as a mechanism for same-race teachers increasing student achievement. These results give a policy recommendation of increased hiring of Black and Hispanic teachers to help Black and Hispanic students while minimally impacting White students.

7.2 Heterogeneity

Next, I explore if race matching in a subject in high school makes a student more likely to major in the subject in college. The distribution of college degrees is not equitable with Black and Hispanic students systematically less likely to major in STEM than their White and Asian counterparts. STEM degrees earn a larger wage premium, so this inequality in STEM degrees further exacerbates wage disparities (Altonji, Blom and Meghir, 2012). I also examine two other majors Social Sciences and English/Writing. I define a STEM degree as a degree with a six-digit Classification of Instructional Programs (CIP) code matching the list of STEM majors designated by the Department of Homeland Security[11]. For English/Writing and Social Sciences, I use two-digit CIP codes to define the major choice[12].

I examine how race matching within certain subjects affects a student's likelihood of majoring in STEM in college as a freshman, conditional on their 9th grade course-set. One may expect there to be an effect for Black and Hispanic students for race matching in STEM courses because of the role model effect, which may be more salient for certain demographics in areas that they are underrepresented like Black and Hispanic students in STEM. I present the results from matching in a given subject in Table 8.

[11] https://www.ice.gov/sites/default/files/documents/Document/2016/stem-list.pdf

[12] For English/Writing courses, I focus on CIP codes involving written or oral communication. Specifically, I use codes 09 and 23. For Social Sciences, I use codes 42, 45, and 59.

Black and Hispanic students increase their likelihood of majoring STEM by 0.7 and 0.6 p.p., respectively, with one additional 9th grade same-race STEM teacher. One additional White English teacher increases the likelihood of a White student majoring in English/Writing by 0.3 p.p.. Finally, an additional same-race Social Science teacher for a Hispanic student increases their likelihood of majoring in Social Sciences by 0.3 p.p.. These heterogeneity results suggest an increased need to hire Black and Hispanic STEM teachers in high school.

Another potential source of heterogeneity is student ability. I examined heterogeneity using 8th grade reading test quartiles at the course-level to tease out the differences in effects for students with different underlying ability. I conduct a similar analysis, splitting the sample into four quartiles of 8th grade reading test scores. I present the analysis in Table 9.

In Panel A, I show the heterogeneity analysis for high school graduation and college enrollment in any college, and in Panel B, I present the results for college enrollment separately for two- and four-year colleges. For Black students, there is a significant increase in the likelihood to graduate high school with an additional race match when they are in the top half of the 8th grade reading test score distribution. For college enrollment, the effect is spread out evenly across the distribution with the top three quartiles becoming more likely to enroll in a four-year college and the bottom quartile becoming more likely to enroll in a two-year college.

For Hispanic students, the same general pattern can be seen with the top section of the distribution becoming more likely to graduate high school and enroll in a four-year college from an additional race match and the bottom two quartiles becoming more likely to enroll in a two-year college. Finally, the race math effect is positively correlated with 8th grade reading test scores for college enrollment for Hispanic students. White students also have a positive correlation in race match effect with the test score distribution for college enrollment.

Asian students see a different pattern for their outcomes. The significant and positive effects come from the bottom of the test score distribution. Asian students in the bottom quartile of 8th grade reading scores become much more likely to graduate from high school or enroll in a two-year college with an additional Asian teacher, but none of the other students are significantly affected. For college enrollment, there is actually a negative effect for a race match for an Asian student at the top quartile of the distribution, driven by a decrease in two-year enrollment. This significant decrease in two-year enrollment is potentially concerning because it is not offset by an increase in four-year college enrollment.

Overall, this heterogeneity analysis sheds further light on the potential mechanism behind role model effects. Given the results of the non-linear dosage model and Gershenson et al. (2018) model, role model effects are present due to the diminishing marginal returns of race matching. One potential way the role model effect could work is through updating students' beliefs about returns to education or their belief in their own abilities. Students may not have attended college despite having sufficient ability to do so because of an incorrect belief about their own ability. Given the race match effects for Black and Hispanic students is concentrated at the top half of the distribution, it gives further credence and evidence to a role model effect dominating.

8 Robustness Checks

8.1 Oster (2019) Bounding

My estimation and identification strategy use institutional knowledge paired with fixed effects to minimize endogenous sorting of students and teachers. However, I am unable to entirely eliminate non-random sorting. There is a non-trivial concern that I am failing to account for some unobservable characteristics that students are sorting along that could result in an omitted variable bias that is biasing my estimate of the true effect of race matching in high school. One potential way to address this concern is to implement the bounding methodology described in Oster (2019), which will allow me to determine how serious this selection could be.

Oster (2019) demonstrates that one is able to evaluate a finding's robustness to omitted variable bias by examining the coefficient and R-squared stability and proves that a consistent bias-adjusted treatment estimation is possible under two assumptions. The first assumption one makes is the relative selection of unobservable and observable characteristics, denoted by δ. Given one cannot examine unobservable selection, one must make an assumption about how much selection occurs on unobservable characteristics. The second assumption is the maximum value of R-squared. She argues for the first assumption that it is reasonable to assume that there is equal selection of observable and unobservable characteristics, i.e. $\delta = 1$. For the maximum value of R-squared, she suggests $R^2_{max} = \min\{\Pi R^2, 1\}$ is reasonable, with Π being a scalar. She shows that randomized results indicate that $\Pi = 1.3$ is appropriate (Oster, 2019). These two assumptions give a bounding set that for a given treatment effect defined as $\Delta = [\tilde{\beta}, \beta^*(R^2_{max}, \delta = 1)]$, such that $\tilde{\beta}$ gives the effect with full controls and β^* gives the bias-adjusted treatment effect.

Ultimately, my fixed effect strategy is leveraging variation at the course level and using fixed effects is akin to selection on observables, making the use of Oster Bounds appropriate. To evaluate how robust the findings are when selecting on student covariates and the high school by year by course or course set fixed effects, I calculate the bounding set Δ for each significant finding. Oster (2019) gives two potential ways of evaluating robustness: 1. if 0 is excluded from bounding set Δ, and 2. if β^* is within the 99.5% confidence interval of $\tilde{\beta}$. I present the bounding sets for each significant result and whether they are robust to either measurement in Table 10 and Table 11.

Out of the 13 significant results examined in the Oster (2019) Bounding analysis, 12 of the results are robust to the bounding set excluding zero, suggesting that the vast majority of the significant results are still different from zero when adjusting for selection on observable and unobservable characteristics. Out of the 13 results, 9 are also robust to being within the 99.5% confidence interval of the original estimate, suggesting that they are sufficiently close to the original estimate. I present the bounding estimates graphically showing the original estimate and the bias-adjusted estimate and how they compare to the two robustness criteria. I present the short-term course-level results on test scores and pass rates in Figure 8, and the long-term results on high school graduation and college enrollment in Figure 9.

It is important to account for the potential omitted variable bias of some unobservable variable driving my results. Given that I cannot fully eliminate sorting along race or other observable characteristics using my fixed effects strategy, it is likely there is also selection on unobservable characteristics. The bounding sets allow me to quantify how important the selection of characteristics is given certain assumptions like equal selection of observable and unobservable characteristics. The table and figures show that my results are largely the same when trying to account for unobservable selection using Oster (2019) with some exception. In particular, the results for test scores and the long-term results for White students are not robust. This lack of robustness for the signficiant linear effects for White students gives further credence to the non-linear results for White students suggesting there is no no significant benefit to White students matching with White teachers.

8.2 Expanding Course-Set to 10th grade

In the main analysis, I use the 9th grade courses that students take to create a course-set to compare students that took identical courses. I focus on 9th grade courses because race matches in 10th, 11th, and 12th grade could be endogenous to the matches in 9th grade if they are a function of the race matches in 9th grade. However, it is possible to still examine the matches in later matches as well. I create 10th grade course-sets to examine if the effect of race matching could vary with a student's age or grade level. I can extend this analysis to 11th and 12th grade as well, but as the grade level becomes higher, the sample size becomes smaller as some students drop out and course offerings become larger, leading to more students without another student with an identical course-set and therefore lacking a comparison.

In Table 12, I present the results using the 10th grade course-set fixed effects in the first panel and the results using a 9th and 10th grade course-set fixed effect in the second panel. The first set of results compares students with identical 10th grade course selections but have different race matches. The second set of results compares students with identical 9th and 10th grade course selections but have different race matches.

The results from using the 10th grade course sets fixed effects are extremely similar to the results using the 9th grade course sets. Black and Hispanic students have significantly better long-term outcomes from race-matches in the 10th grade. The magnitude of the results is slightly higher than the effect of 9th grade race-matches, but they are statistically indistinguishable from each other. Asian students appear to not benefit from 10th grade race-matches, while significantly becoming more likely to graduate high school from 9th grade race-matches. Finally, White students become more likely to enroll in college following 10th grade race matches in a slightly smaller magnitude compared to 9th grade race matches.

9 Discussion

One noticeable difference between the short-term course-level outcomes and the longer-term individual-level outcomes is the difference in who is affected. Black students benefit from matching in both long- and short-term outcomes, but this is not true for all of the students. Asian students benefit in the short-term from a race match but are not as affected in the long-term, which is the reverse for Hispanic students receiving a race match, who benefit in the long-term from a race match but do not benefit in the short-term.

There exists a disconnect between the short-term course results and long-term individual results. Black and Asian students benefit modestly in the short-term by having slightly higher test scores and pass rates. However, Black students see much larger gains in the long-term from race matches with large increases in their likelihood to enroll in college that seem disproportionately large to their short-term benefits. Black students become 0.9 p.p.

more likely to pass their classes with Black teachers and 1 percentage point more likely to enroll in a four-year college after one additional 9th grade Black teacher. These outcomes are different educational achievement measures and are not directly comparable, but it still seems unlikely that improving the pass rate by a small amount would result in a large effect size for college enrollment. It could mean that same-race teachers also increase non-cognitive measures of students that impact expectations and beliefs that are not directly picked up in measurement like test scores or pass rates. This implication is consistent with past research into expectations, behavior, and beliefs[13].

This disconnect between long- and short-term effects seems counterintuitive as one may expect a student to benefit the most the closer they are to the treatment than further away. However, this finding is consistent with the only other paper in the literature examining long term effects of race matching. Gershenson et al. (2018) find a 4 percentage point increase in college enrollment with an additional Black K-3 teacher for Black students, while I find a 1 percentage point increase from an additional 9th grade Black teacher. My results taken with Gershenson et al. (2018) suggest that the effect of race matching may be stronger in the long-term. This difference between short-term and long-term effects suggest different mechanisms affecting short- and long-term outcomes.

One potential reason for the differences in results is that in the short-term outcomes, the relative frequency of teachers is important for having an effect. Black and Asian students are the smallest minority groups with Hispanic and White students comprising the two largest ethnic groups in Texas. There are also many more Hispanic and White teachers than there are Asian and Black teachers. However, there are no significant effects for Asian students in the long-term outcomes for college enrollment. The long-term linear effects of race matching for college enrollment had effects for each race except that with the highest achievement - Asian students.

It may be that in the short-term there are strong effects from "culturally relevant peda-

[13](Fox (2015); Papageorge, Gershenson and Kang (2018))

gogies" such as having different interactions that are culturally relevant to Black and Asian students that only same-race teachers would understand. There has been research into how culturally relevant pedagogies affect Black students (Irvine (1990); Ladson-Billings (1995)). Another potential effect from race matching is a role model effect wherein role models may get students to update their beliefs about human capital accumulation (Marx and Roman (2002); Dee (2005)). Research shows that having a same-race teacher can raise a student's expectations on achieving higher education (Fox (2015); Papageorge, Gershenson and Kang (2018)). Importantly, these theories about how race matching could improve students outcomes are not mutually exclusive but likely work in conjunction with one another, with a culturally relevant pedagogy feeding into role model effects and vice-versa.

Overall, the results are consistent with a story of culturally relevant pedagogies more strongly affecting short-term outcomes and role model effects impacting longer-term outcomes. The culturally relevant pedagogies would likely be strongest with students that have the least representation for teachers as is the case for Black and Asian students, while the role model effects would impact the lower achieving groups more such as Black, Hispanic, and White students. Specifically, the impact of race matching for long-term outcomes like college enrollment are largest for Black and Hispanic students who would have the biggest impact on their educational expectations. My results further validate this hypothesis when looking at the non-linear effects of dosage for race matching in long-term outcomes. Following the model developed in Gershenson et al. (2018), diminishing marginal returns of same-race teachers would imply that role-model effects dominate over increased effectiveness of same-race instruction.

Racial gaps in educational attainment have been documented in many different settings, and Texas is no exception. Black and Hispanic students lag behind their White peers who also lag behind their Asian peers in educational outcomes. Race-matching appears to significantly decrease the race gap between underrepresented minorities and White students. For instance, an additional Black teacher match reduces the Black-White college enrollment gap by 11%, and an additional Hispanic teacher match reduces the Hispanic-White high school graduation and college enrollment gap by 14% and 11%, respectively.

Race-matching for White students on the other hand appears to have no robust effect on White student outcomes. While there is a positive effect for White students in the linear dosage model, I show in the Robustness Check section that those results are not robust to Oster (2019) and her bounding methodology. Specifically, the outcomes for White students are the only results that are not robust to the bounding strategy. When relaxing the linearity assumption and allowing the effect to be more flexible, White students no longer benefit from race-matching. Overall, the evidence in this paper suggests that White students do not benefit significantly from race-matching and that one could replace White teachers with more Black and Hispanic teachers to the benefit of Black and Hispanic students without making White students any worse off.

The effect sizes of the race matches for Black and Hispanic students seem fairly large. The results indicate that one additional Black match increases college enrollment for Black students by 1 percentage point, and one additional Hispanic match increases college enrollment for Hispanic students by 1.5 p.p.. It's difficult to compare these results to the literature as there is only one other paper that directly observes long-term outcomes from matches. Gershenson et al. (2018) uses the Tennessee STAR randomized teacher-student assignment in elementary school to examine race matches of Black students and teachers. The randomization element should create unbiased estimates of these long-term effects of matches, providing an excellent comparison. They find that Black students randomly assigned to one Black teacher in grades K-3 are 4 p.p. more likely to enroll in college, an effect size about four times my effect size. It's not an exact comparison though as Gershenson et al. (2018) look at elementary school matching, and I examine high school race matching. This distinct difference in timing of the race-matches informs the broader education literature as well. Heckman argues that treatment effects can have larger impacts when children are younger as these skills can build on top of each other (Heckman 1999). One may be concerned that in high school it is too late to change the trajectory of a student's educational career from additional same-race teachers. I confirm Heckman's hypothesis in this setting showing the effect sizes are smaller but are still significant in high school. Using Gershenson et al. (2018) and their randomization as a reference point for an earlier intervention suggest that I find a plausible effect size.

10 Conclusion

I present evidence showing that race matching in high school can significantly impact racial gaps that exist in high school and college achievement. I control for non-random sorting better than past studies by exploiting institutional details and using course-level fixed effects. I reduce non-random sorting of students to same-race teachers by about 99% for Black, Hispanic, and White students. Only one Gershenson et al. (2018) has examined the effects of race matching on high school graduation and college enrollment but does not examine Hispanic or Asian students, which my paper sheds new light on. I present the first evidence of high school student-teacher race matching effects. Race matching for Black and Hispanic students significantly decreases race gaps. An additional same-race 9th grade teacher for Black and Hispanic students increases their likelihood to enroll in college by 1 and 1.5 p.p., respectively. In my heterogeneity analysis, I also show that Black and Hispanic students become significantly more likely to major in a STEM field as freshmen in college after having a Black or Hispanic STEM teacher.

While I find significant effects for White students in the linear dosage model, these results are not robust to the bounding methodology outlined in Oster (2019). Furthermore, the non-linear dosage model shows that White students do not benefit from race-matching across all outcomes. These results taken with the results for Black and Hispanic students suggest that hiring more Black and Hispanic teachers could greatly improve academic achievement for Black and Hispanic students while having minimal negative tradeoffs for White students. A policy aimed at decreasing racial gaps in education should target training and hiring Black and Hispanic teachers with a focus on STEM teachers.

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Table 1: Descriptive Statistics

Panel A: Student Characteristics

Variable	Black Mean	Hispanic Mean	Asian Mean	White Mean
HS Grad	0.777	0.787	0.898	0.830
Enroll Any	0.455	0.409	0.662	0.532
Enroll two-year	0.277	0.280	0.353	0.318
Enroll four-year	0.188	0.142	0.423	0.234
STEM Major	0.073	0.083	0.260	0.114
Test Z-Score	-0.107	-0.049	0.834	0.401
Pass Rate	0.872	0.858	0.970	0.939
Female	0.499	0.494	0.489	0.488
At Risk	0.696	0.702	0.301	0.425
Gifted	0.059	0.085	0.250	0.114
Free/Reduced Price Lunch	0.738	0.800	0.368	0.425
n	88,668	323,067	26,438	215,661

Panel B: Student and Teacher Composition

Variable	Black Mean	Hispanic Mean	Asian Mean	White Mean
Student Composition	0.137	0.498	0.041	0.332
Teacher Composition	0.091	0.183	0.023	0.702

Descriptive statistics showing student achievement, characteristics, and composition for Texas high school students in 2012 and 2013 9th grade cohort. Panel A shows student characteristics and outcomes at the student level. Panel B shows student and teacher racial composition at the state level. Data comes from the Texas Education Research Center linking Texas public high school data to Texas and national college data.

Table 2: Race-Matching Effects on Course-level Outcomes

VARIABLES	(1) Test Z-Score		(2) Pass	
	Estimate	Mean	Estimate	Mean
Black Match	0.013***	-0.107	0.009***	0.872
	(0.004)		(0.001)	
Hispanic Match	0.003	-0.049	0.001	0.858
	(0.004)		(0.001)	
Asian Match	0.070***	0.834	0.014***	0.970
	(0.021)		(0.002)	
White Match	0.001	0.401	-0.0003	0.939
	(0.004)		(0.0007)	
Observations	2,268,544		8,955,014	
R-squared	0.786		0.443	

This table shows the effect of race matching at the course level on course-level outcomes using student, teacher, and high school by year by course fixed effects. There are fewer observations for the test scores as standardized tests are only administered in five courses while every course designates whether a student passes. "Test Z-Score" measure is in terms of standard deviations, and the Match terms are interpreted as changes in a standard deviation. Pass is an indicator for if a student passes the course, and the Match terms are interpreted as a percentage point change. Race specific means are next to the estimated effect for context. Standard errors are clustered at the school level.

Table 3: Heterogeneity Effects of Race-Matching by 8th Grade Reading Test Scores

VARIABLES	(1) Test Z-Score				(2) Pass			
	Black Match	Hispanic Match	Asian Match	White Match	Black Match	Hispanic Match	Asian Match	White Match
8th Grade Reading Test Scores								
Top Quartile	0.003	-0.004	0.052**	0.006	0.005**	-0.001	0.015***	-0.001
	(0.009)	(0.007)	(0.022)	(0.006)	(0.002)	(0.001)	(0.003)	(0.001)
2nd Quartile	0.012*	-0.001	0.054*	-0.004	0.008***	-0.0003	0.011***	0.0001
	(0.007)	(0.005)	(0.032)	(0.006)	(0.002)	(0.001)	(0.003)	(0.001)
3rd Quartile	0.014**	0.004	0.098***	0.003	0.009***	0.0016	0.015***	-0.001
	(0.006)	(0.005)	(0.035)	(0.006)	(0.002)	(0.001)	(0.004)	(0.001)
Bottom Quartile	0.016**	0.010*	0.095*	-0.0004	0.013***	0.003**	0.017***	0.001
	(0.007)	(0.006)	(0.057)	(0.006)	(0.002)	(0.001)	(0.003)	(0.002)
Observations	2,268,544				8,955,014			
R-squared	0.786				0.443			

This table shows the effect of race matching at the course level on course-level outcomes using student, teacher, and high school by year by course fixed effects. The regressions are broken into quartiles of 8th grade math test scores. There are fewer observations for the test scores as standardized tests are only administered in five courses while every course designates whether a student passes. "Test Z-Score" measure is in terms of standard deviations, and the Match terms are interpreted as changes in a standard deviation. Pass is an indicator for if a student passes the course, and the Match terms are interpreted as a percentage point change. Standard errors are clustered at the school level.

Table 4: Descriptive Statistics: Dosage Model

Panel A: Student Characteristics

Variable Mean	Black	Hispanic	Asian	White
HS Grad	0.597	0.668	0.718	0.711
Enroll Any	0.488	0.438	0.678	0.562
Two-Year Enroll	0.291	0.298	0.357	0.33
Four-Year Enroll	0.21	0.157	0.443	0.255
STEM Major	0.081	0.091	0.27	0.122
Total Teachers	4.2	4.3	4.2	4.3
Number of Race Matches	0.902	1.37	0.155	3.74
Obs	66,826	246,450	22,302	175,912

Panel B: Student and Teacher Composition

Variable Mean	Black	Hispanic	Asian	White
Student Composition	0.125	0.460	0.042	0.329
Teacher Composition	0.089	0.182	0.021	0.703

Descriptive statistics showing student achievement, characteristics, and composition for Texas high school students in 2012 and 2013 9th grade cohort in the dosage model. Panel A shows student characteristics and outcomes at the student level. Panel B shows student and teacher racial composition at the state level. Data comes from the Texas Education Research Center linking Texas public high school data to Texas and national college data.

Table 5: Linear Dosage Effects of Race Matching of 9th Grade Teachers

Panel A: Course-Set Fixed Effects

VARIABLES	(1) HS Grad		(2) Enroll Any		(3) Enroll Two-Year		(4) Enroll Four-Year	
	Estimate	Mean	Estimate	Mean	Estimate	Mean	Estimate	Mean
Black Match	0.003	0.597	0.010***	0.488	0.003	0.291	0.010***	0.210
	(0.003)		(0.003)		(0.002)		(0.002)	
Hispanic Match	0.007***	0.668	0.015***	0.438	0.007**	0.298	0.009***	0.157
	(0.002)		(0.003)		(0.003)		(0.002)	
Asian Match	0.018**	0.718	-0.015	0.678	-0.002	0.357	-0.011	0.443
	(0.008)		(0.015)		(0.012)		(0.010)	
White Match	0.001	0.711	0.007***	0.562	0.004**	0.330	0.002	0.255
	(0.002)		(0.002)		(0.002)		(0.001)	
Observations	514,501		514,501		514,501		514,501	
R-squared	0.36		0.232		0.122		0.257	

Panel B: Cohort Course-Set Fixed Effects

VARIABLES	(1) HS Grad		(2) Enroll Any		(3) Enroll Two-Year		(4) Enroll Four-Year	
	Estimate	Mean	Estimate	Mean	Estimate	Mean	Estimate	Mean
Black Match	0.003	0.597	0.010***	0.488	0.003	0.291	0.009***	0.210
	(0.003)		(0.003)		(0.003)		(0.002)	
Hispanic Match	0.007***	0.668	0.016***	0.438	0.008***	0.298	0.010***	0.157
	(0.002)		(0.003)		(0.003)		(0.002)	
Asian Match	0.017**	0.718	-0.012	0.678	-0.003	0.357	-0.01	0.443
	(0.008)		(0.015)		(0.011)		(0.010)	
White Match	0.002	0.711	0.007***	0.562	0.003*	0.330	0.002	0.255
	(0.002)		(0.002)		(0.002)		(0.002)	
Observations	506,034		506,034		506,034		506,034	
R-squared	0.376		0.248		0.141		0.274	

This table provides the results from the linear dosage model for 9th grade race matches conditional on course-set or cohort course-set fixed effects. The fixed effects make comparisons between students that took identical courses in the same high school but have different race teachers. The interpretation on the Match coefficient is the effect of one additional same-race teacher. Race specific means are next to the estimate for context. Panel A displays the effect using course-set fixed effects while Panel B shows the cohort course-set fixed effects. Standard errors are clustered at the high school level.

Table 6: Non-linear Match Effects for HS Graduation and College Enrollment

VARIABLES	(1) HS Grad				(2) Enroll Any			
	Black Match	Hispanic Match	Asian Match	White Match	Black Match	Hispanic Match	Asian Match	White Match
Match == 1	0.003	0.006*	0.019**	-0.02	0.007	0.014***	-0.003	-0.027
	(0.005)	(0.003)	(0.009)	(0.015)	(0.006)	(0.004)	(0.012)	(0.021)
Match == 2	-0.001	0.011**	0.023	0.008	0.024***	0.034***	-0.076	-0.003
	(0.007)	(0.006)	(0.028)	(0.015)	(0.008)	(0.008)	(0.060)	(0.020)
Match == 3	0.004	0.014*	0.075	0.015	0.036***	0.046***	-0.190*	0.011
	(0.008)	(0.009)	(0.076)	(0.015)	(0.010)	(0.011)	(0.110)	(0.019)
Match == 4	0.009	0.016	-	0.017	0.025*	0.056***	-	0.022
	(0.014)	(0.010)	-	(0.015)	(0.014)	(0.015)	-	(0.019)
Match == 5	0.057**	0.023*	-	0.005	0.047*	0.062***	-	0.015
	(0.029)	(0.013)	-	(0.015)	(0.028)	(0.019)	-	(0.020)
Match == 6	0.087**	0.045**	-	-0.005	0.012	0.056**	-	-0.002
	(0.035)	(0.018)	-	(0.018)	(0.047)	(0.024)	-	(0.023)
Observations	514,501				514,501			
R-squared	0.360				0.232			

This table shows the results of the non-linear dosage model for 9th grade race matches conditional on course-set on high school graduation and any college enrollment. I regress indicators for each number of race match on outcomes allowing the functional form to be flexible to test for non-linearity. The omitted group for each race is the no matches group, putting the coefficients in reference to no matches. No Asian students have more than 3 race matches. The fixed effects make comparisons between students that took identical courses in the same high school but have different race teachers. The coefficients are plotted in Figure 6. Standard errors are clustered at the high school level.

Table 7: Non-linear Match Effects for Two- and Four-Year College Enrollment

VARIABLES	(3) Enroll Two-Year				(4) Enroll Four-Year			
	Black Match	Hispanic Match	Asian Match	White Match	Black Match	Hispanic Match	Asian Match	White Match
Match == 1	-0.002	0.006*	-0.003	-0.012	0.017***	0.008***	0.008	-0.025
	(0.005)	(0.004)	(0.011)	(0.019)	(0.005)	(0.003)	(0.010)	(0.016)
Match == 2	0.002	0.020***	-0.003	0.003	0.035***	0.017***	-0.121***	-0.014
	(0.007)	(0.006)	(0.049)	(0.018)	(0.006)	(0.006)	(0.022)	(0.014)
Match == 3	0.012	0.021**	-0.035	0.011	0.027***	0.028***	-0.08	-0.003
	(0.011)	(0.009)	(0.064)	(0.018)	(0.008)	(0.007)	(0.097)	(0.014)
Match == 4	0.013	0.022*	-	0.017	0.013	0.038***	-	-0.002
	(0.013)	(0.011)	-	(0.018)	(0.010)	(0.010)	-	(0.014)
Match == 5	0.039**	0.02	-	0.013	0.022	0.047***	-	-0.007
	(0.019)	(0.016)	-	(0.018)	(0.018)	(0.014)	-	(0.015)
Match == 6	0.001	0.007	-	0.001	0.004	0.052***	-	-0.016
	(0.054)	(0.019)	-	(0.021)	(0.018)	(0.018)	-	(0.017)
Observations	514,501				514,501			
R-squared	0.122				0.258			

This table shows the non-linear dosage model for 9th grade race matches conditional on course-set on two- versus four-year college enrollment. I regress indicators for each number of race match on outcomes allowing the functional form to be flexible to test for non-linearity. The omitted group for each race is the no matches group, putting the coefficients in reference to no matches. Asian students do not have more than 3 race matches. The fixed effects make comparisons between students that took identical courses in the same high school but have different race teachers. The coefficients are plotted in Figure 7. Standard errors are clustered at the high school level.

Table 8: Dosage Effects of Race Matching in STEM Courses

VARIABLES	(1) STEM Major	(2) Writing Major	(3) Social Science Major
Black Subject Match	0.007***	0.001	0.001
	(0.003)	(0.001)	(0.002)
Hispanic Subject Match	0.006***	-0.001*	0.003**
	(0.002)	(0.001)	(0.001)
Asian Subject Match	-0.006	0.005	-0.007
	(0.010)	(0.007)	(0.008)
White Subject Match	0.0004	0.003***	0.00001
	(0.002)	(0.001)	(0.001)
Observations	514,501	514,501	514,501
R-squared	0.174	0.091	0.096

This table show the results from the dosage model for 9th grade race matches examining heterogeneity in subject conditional on course-set fixed effects. The fixed effects make comparisons between students that took identical courses in the same high school but have different race teachers. The interpretation on the Match coefficients is the effect of one additional same-race teacher in a given subject such as STEM, English, or Social Science. Standard errors are clustered at the high school level.

Table 9: Heterogeneity of 8th Reading Scores in Dosage Model

Panel A: HS Grad and Enrollment								
	(1)				(2)			
VARIABLES	Effect of Race Match on HS Grad				Effect of Race Match on Enroll Any			
	Black	Hispanic	Asian	White	Black	Hispanic	Asian	White
8th Grade Reading Test Scores								
Top Quartile	0.008**	0.009***	0.002	0.003*	0.012**	0.023***	-0.054***	0.010***
	(0.004)	(0.002)	(0.012)	(0.002)	(0.005)	(0.004)	(0.016)	(0.002)
2nd Quartile	0.011***	0.008***	0.014	0.002	0.009***	0.016***	0.004	0.009***
	(0.004)	(0.002)	(0.012)	(0.002)	(0.003)	(0.004)	(0.020)	(0.002)
3rd Quartile	-0.001	0.008***	0.015	-0.001	0.011***	0.014***	0.037*	0.004**
	(0.003)	(0.002)	(0.014)	(0.002)	(0.003)	(0.003)	(0.020)	(0.002)
Bottom Quartile	0.0004	0.002	0.076***	-0.001	0.010***	0.010***	0.008	0.001
	(0.004)	(0.003)	(0.019)	(0.002)	(0.004)	(0.004)	(0.022)	(0.002)
Observations	514,501				514,501			
R-squared	0.361				0.232			
Panel B: Two- vs Four- Year Enrollment								
	(3)				(4)			
VARIABLES	Effect of Race Match on Enroll Two-Year				Effect of Race Match on Enroll Four-Year			
	Black	Hispanic	Asian	White	Black	Hispanic	Asian	White
8th Grade Reading Test Scores								
Top Quartile	0.005	0.006**	-0.036***	0.005***	0.012***	0.018***	-0.011	0.003*
	(0.004)	(0.003)	(0.014)	(0.002)	(0.004)	(0.003)	(0.016)	(0.002)
2nd Quartile	-0.006*	0.005	-0.008	0.004*	0.023***	0.013***	0.02	0.004***
	(0.003)	(0.003)	(0.016)	(0.002)	(0.003)	(0.002)	(0.016)	(0.002)
3rd Quartile	0.0003	0.008***	0.047**	0.003	0.011***	0.007***	-0.007	0.001
	(0.003)	(0.003)	(0.020)	(0.002)	(0.002)	(0.002)	(0.022)	(0.002)
Bottom Quartile	0.011***	0.008***	0.053**	0.003	-0.0004	0.003	-0.076***	-0.003
	(0.003)	(0.003)	(0.024)	(0.002)	(0.002)	(0.002)	(0.013)	(0.002)
Observations	514,501				514,501			
R-squared	0.123				0.259			

This table presents the linear dosage model for 9th grade race matches conditional on course-set effects examining heterogeneity in ability. The regressions are broken into quartiles of 8th grade math test scores. The fixed effect makes comparisons between students that took identical courses in the same high school but have different race teachers. The interpretation on the Match coefficient is the effect of one additional same-race teacher for a given student in a 8th grade math score quartile. Standard errors are clustered at the high school level.

Table 10: Course-level Bounding Set for Estimates

	Test Scores			
	Estimate	Bias-Adjusted	Robust to Excluding Zero	Robust to 99.5% CI
Black Match	0.013***	0.0558	X	
Hispanic Match				
Asian Match	0.070***	-0.0263		
White Match				
	Pass Rate			
	Estimate	Bias-Adjusted	Robust to Excluding Zero	Robust to 99.5% CI
Black Match	0.0091***	0.008246	X	X
Hispanic Match				
Asian Match	0.014***	0.013051	X	X
White Match				

This table presents the bounding set for each of my significant results in short-term course-level outcomes when accounting for selection of observable and unobservable characteristics using Oster (2019). The first column shows the coefficient I estimate using the full model, and the second column shows the bias-adjusted estimate using Oster (2019). The last two columns evaluate if the bounding set is robust to excluding zero or if the bias-adjusted estimate is within a 99.5% confidence interval of the original estimate. These esimates are plotted in Figure 8

.

Table 11: Individual-level Bounding Set for Estimates

	Estimate	Bias-Adjusted	Robust to Excluding Zero	Robust to 99.5% CI
HS Graduation				
Black Match				
Hispanic Match	0.007***	0.008	X	X
Asian Match	0.018**	0.009	X	X
White Match				
Enroll Any				
Black Match	0.010***	0.009	X	X
Hispanic Match	0.015***	0.006	X	X
Asian Match				
White Match	0.007***	0.017	X	
Enroll Two-Year				
Black Match				
Hispanic Match	0.007**	0.001	X	X
Asian Match				
White Match	0.004**	0.011	X	
Enroll Four-Year				
Black Match	0.010***	0.005	X	X
Hispanic Match	0.009***	0.005	X	X
Asian Match				
White Match				

This table presents the bounding set for each of my significant results in the linear dosage model when accounting for selection of observable and unobservable characteristics using Oster (2019). The first column shows the coefficient I estimate using the full model, and the second column shows the bias-adjusted estimate using Oster (2019). The last two columns evaluate if the bounding set is robust to excluding zero or if the bias-adjusted estimate is within a 99.5% confidence interval of the original estimate. These esimates are plotted in Figure 9

.

Table 12: Expanded Course Sets

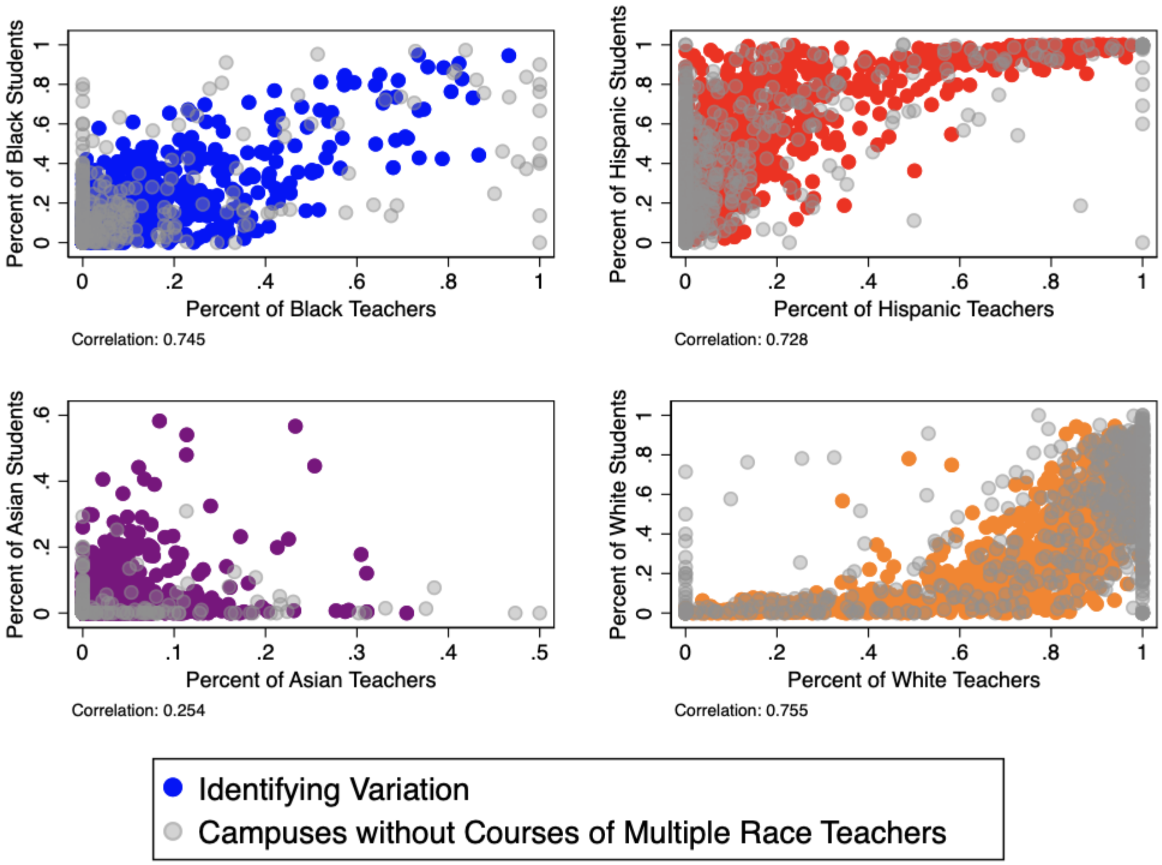
Panel A: 10th Grade Course Set				
	(1)	(2)	(3)	(4)
VARIABLES	HS Grad	Enroll Any	Two-Year Enroll	Four-Year Enroll
Black Match	0.003	0.013***	0.005*	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
Hispanic Match	0.004*	0.018***	0.011***	0.008***
	(0.002)	(0.003)	(0.003)	(0.002)
Asian Match	0.007	0.011	0.01	0.008
	(0.006)	(0.011)	(0.008)	(0.010)
White Match	0.002	0.005**	0.005***	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	407,727	407,727	407,727	407,727
R-squared	0.321	0.286	0.195	0.323

Panel B: 9th and 10th Grade Course Set				
	(1)	(2)	(3)	(4)
VARIABLES	HS Grad	Enroll Any	Two-Year Enroll	Four-Year Enroll
Black Match	0.001	0.008***	0.0005	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic Match	0.002*	0.010***	0.007***	0.005***
	(0.001)	(0.002)	(0.002)	(0.002)
Asian Match	0.0002	0.003	0.006	0.003
	(0.001)	(0.010)	(0.009)	(0.008)
White Match	0.003***	0.004***	0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	317,979	317,979	317,979	317,979
R-squared	0.564	0.393	0.28	0.392

This table shows the dosage model for 10th grade race matches or 9th and 10th grade race matches conditional on course-set fixed effects. The fixed effects make comparisons between students that took identical courses in the same high school but have different race teachers. The interpretation on the Match coefficient is the effect of one additional same-race teacher. Standard errors are clustered at the high school level.

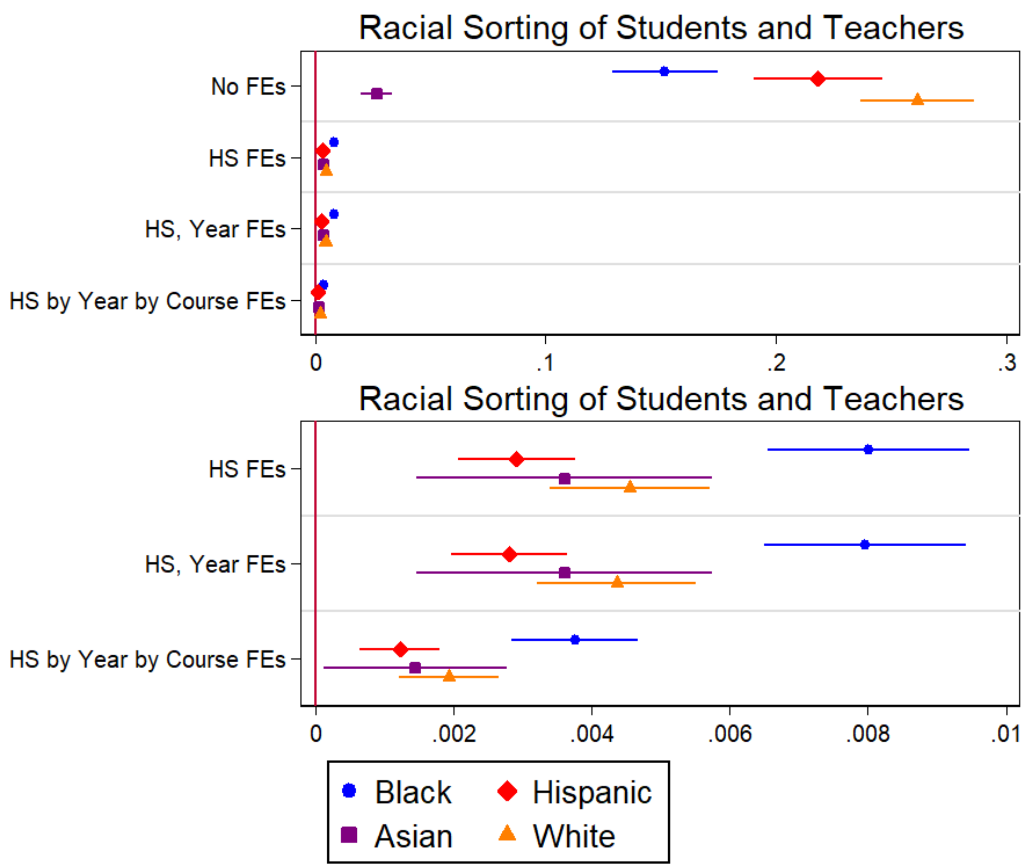
Figures

Figure 1: Campus Level Identifying Variation



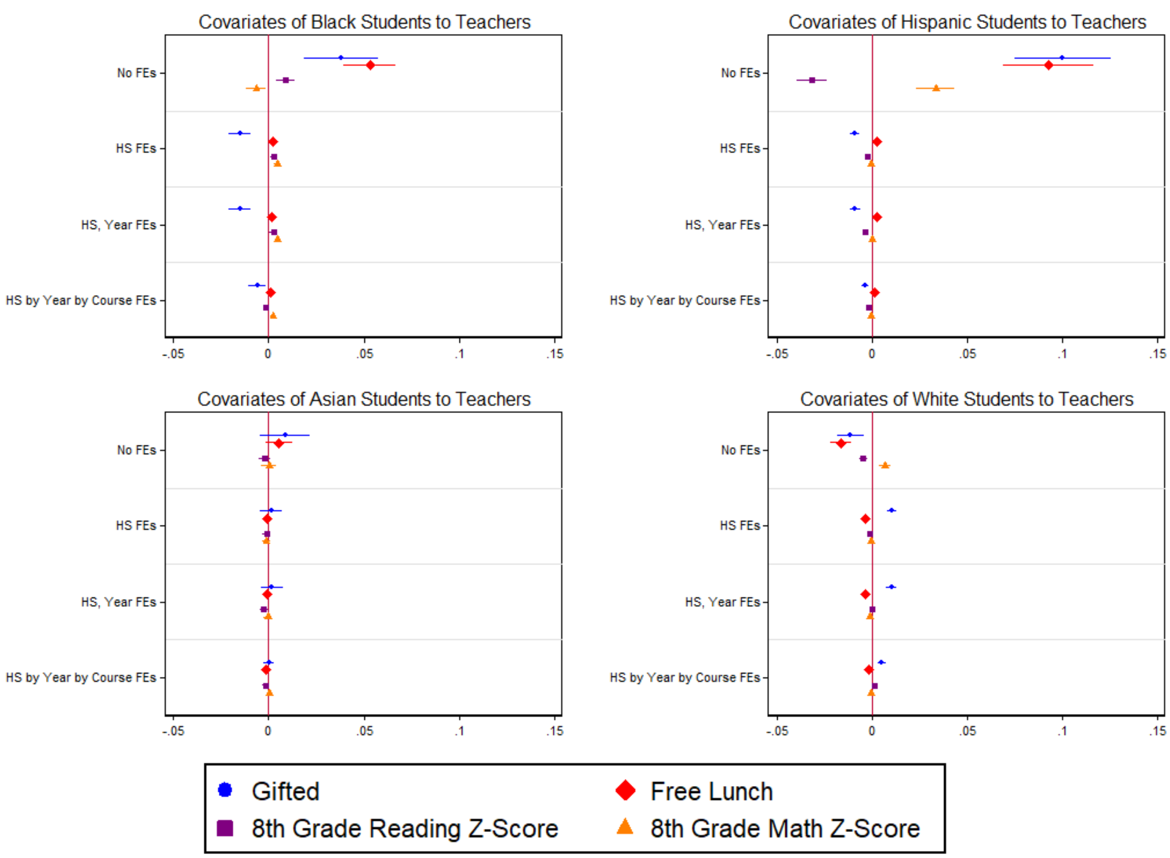
Note: These figures plot the relationship at the campus level between students and teachers of the same race. The top left quadrant shows Black students and teachers, the top right quadrant shows Hispanic students and teachers, the bottom left quadrant shows Asian students and teachers, and the bottom right quadrant shows White students and teachers. The gray dots shows campuses that do not contribute to the identifying variation in that they do not have courses with multiple race teachers. The correlation coefficient for each race is given below each plot.

Figure 2: Likelihood of Same-Race Student Teacher Sorting



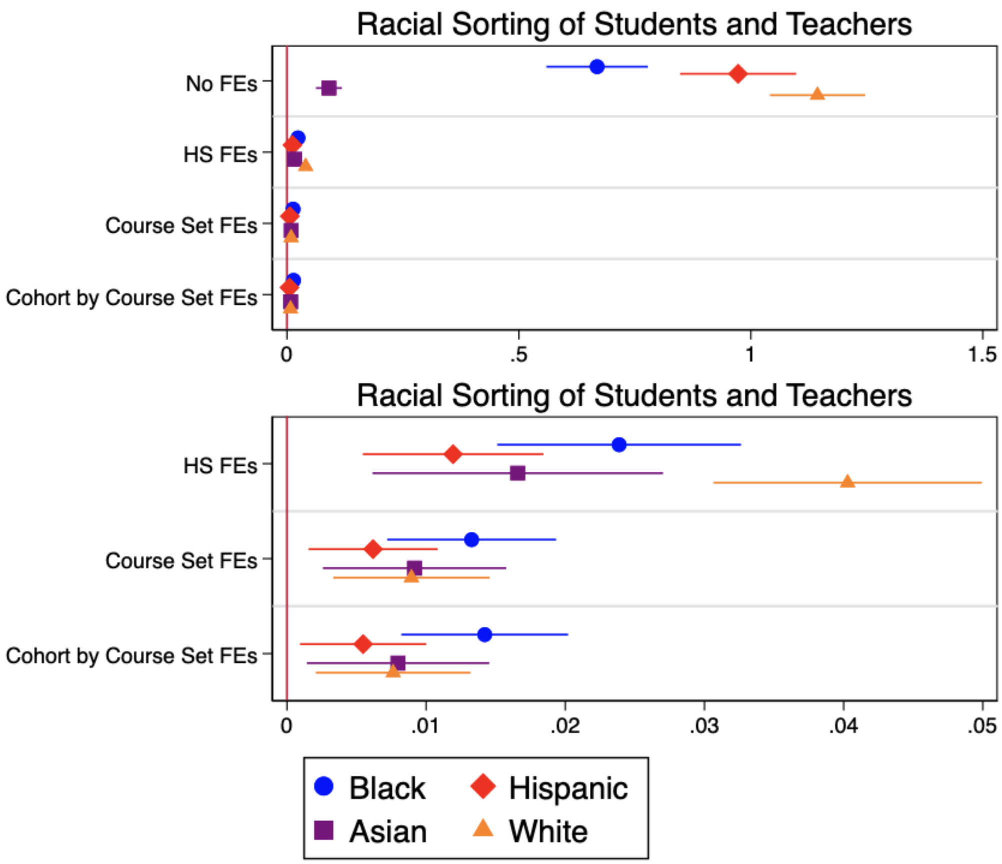
Note: These figures plot the coefficients estimated using regressions (1)-(4) estimated separately using varying fixed effects to estimate the likelihood that students and teachers are matched along racial lines. The top and bottom figure display the same information and coefficents, but the bottom figure omits the "No FEs" model to show the scaling between the last three models. Racial sorting of students and teachers decreases with high school FEs and decreases further using high school by year by course FEs. Standard errors are clustered at the school level.

Figure 3: Covariates that Predict Same-Race Student Teacher Assignment



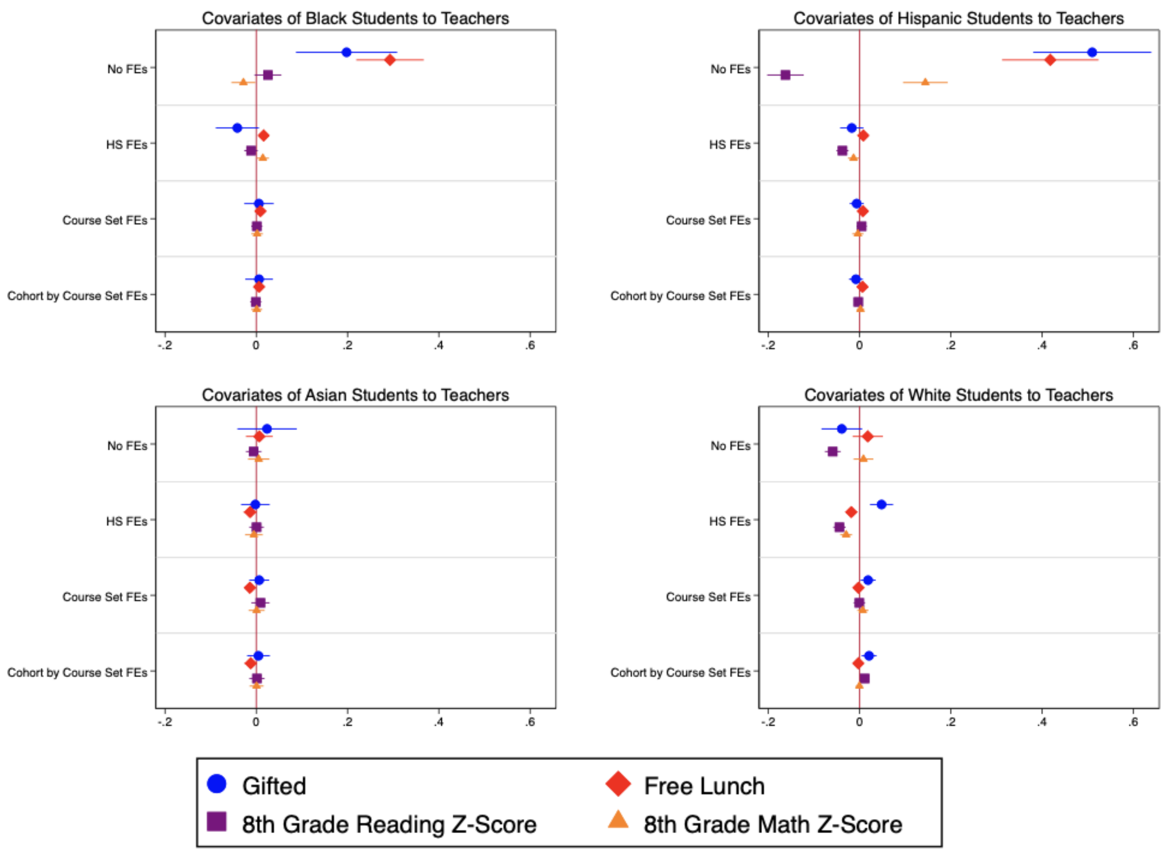
Note: These figures plot the coefficients estimated using regression (5)-(8) estimated separately using varying fixed effects to estimate what covariates predict students and teachers matching along racial lines. Regressions are limited to one race to examine how the covariates for students of that race predict race matching. Racial sorting of students and teachers decreases with high school FEs and decreases further using high school by year by course FEs. Standard errors are clustered at the school level.

Figure 4: Dosage – Likelihood of Same-Race Student Teacher Sorting



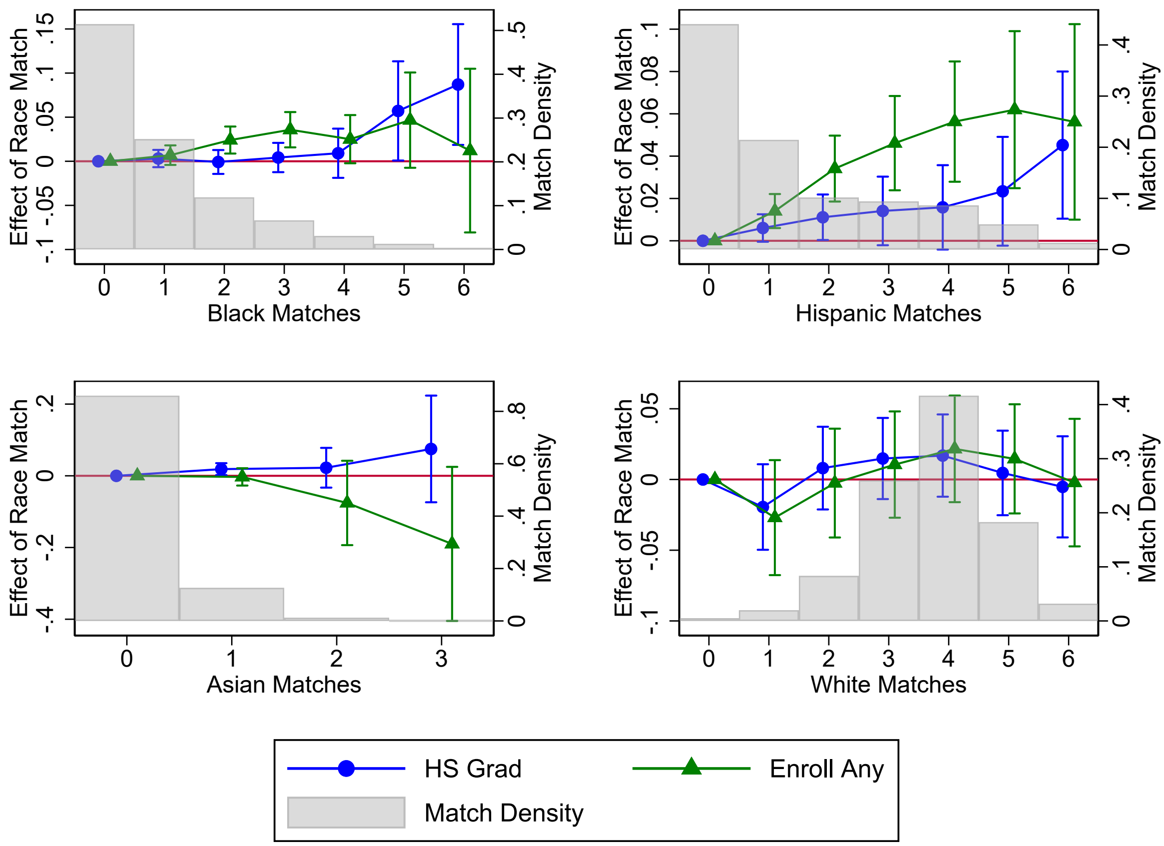
Note: These figures plot the coefficients estimated using regression (10)-(13) estimated separately using varying fixed effects to estimate the likelihood that students and teachers are matched along racial lines. The top and bottom figure display the same information and coefficents, but the bottom figure omits the "No FEs" model to show the scaling between the last three models. Racial sorting of students and teachers decreases with high school FEs and decreases further using course-set FEs. Standard errors are clustered at the school level.

Figure 5: Dosage – Covariates that Predict Same-Race Student Teacher Assignment



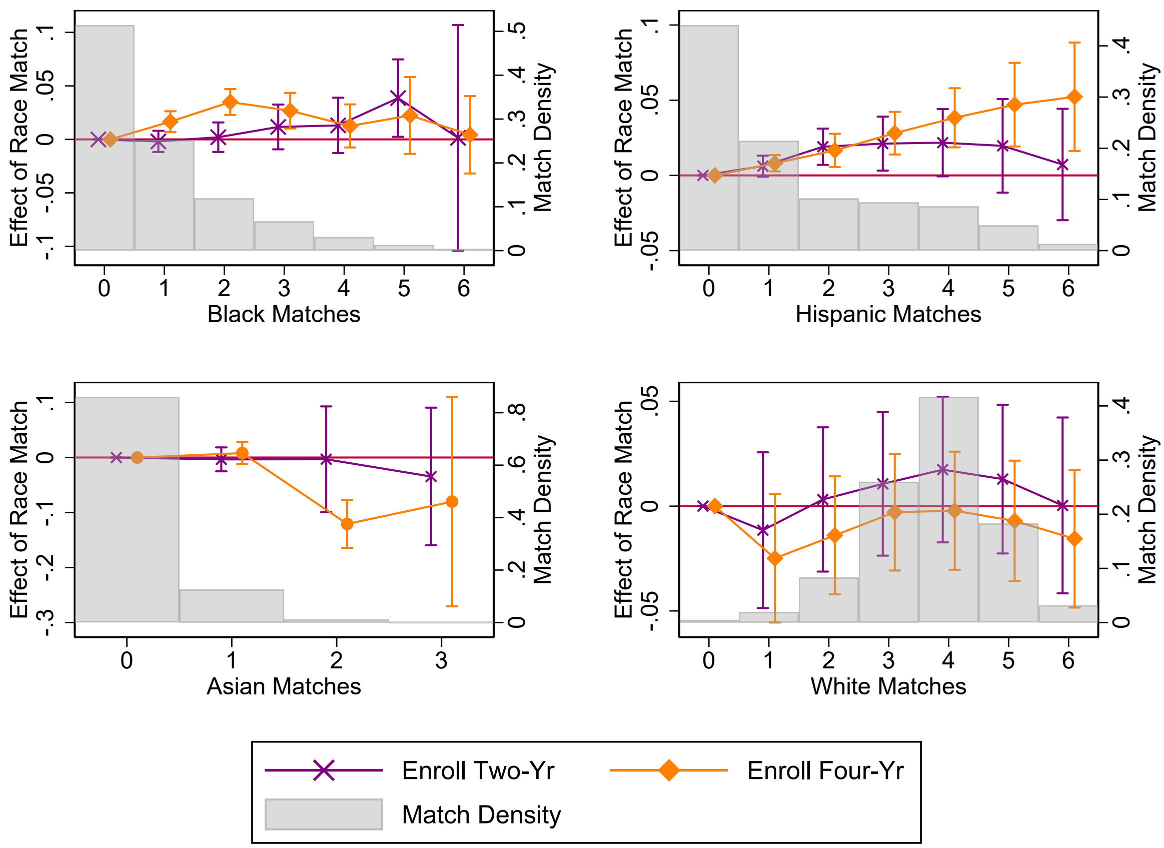
Note: These figures plot the coefficients estimated using regression (14)-(17) estimately separately using varying fixed effects to estimate what covariates predict students and teachers matching along racial lines. Regressions are limited to one race to examine how the covariates for students of that race predict race matching. Racial sorting of students and teachers decreases with high school FEs and decreases further using course-set FEs. Standard errors are clustered at the school level.

Figure 6: Non-linear Race Match Effects on HS Graduation and College Enrollment



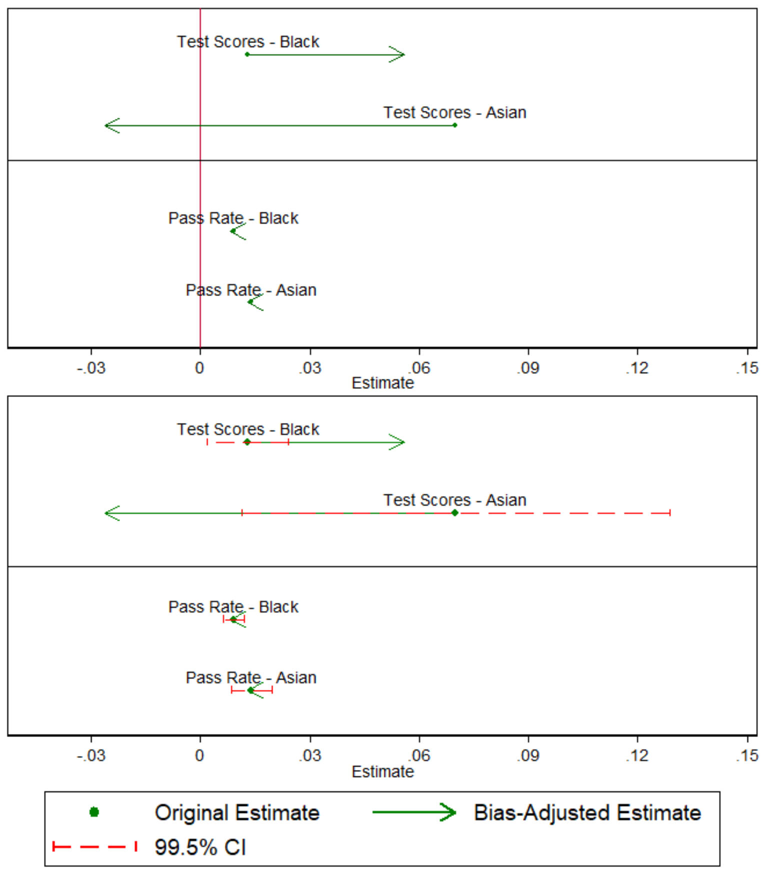
Note: These plots show the non-linear race match effects for high school graduation and college enrollment. The top left quadrant shows the non-linear effects for Black students, the top right quadrant shows the effects for Hispanic students, the bottom left quadrant shows the effects for Asian students, and the bottom right quadrant shows the effects for White students. The group for no race matches is omitted as the reference group. For context, I include the histogram for race-matches for each race in the plot to determine how the support for each plot varies by race. The left y-axis scales the effect size and the right y-axis scales the histogram. The coefficients are displayed in Table 6. Standard errors are clustered at the school level.

Figure 7: Non-linear Race Match Effects on Two- vs Four-Year College Enrollment



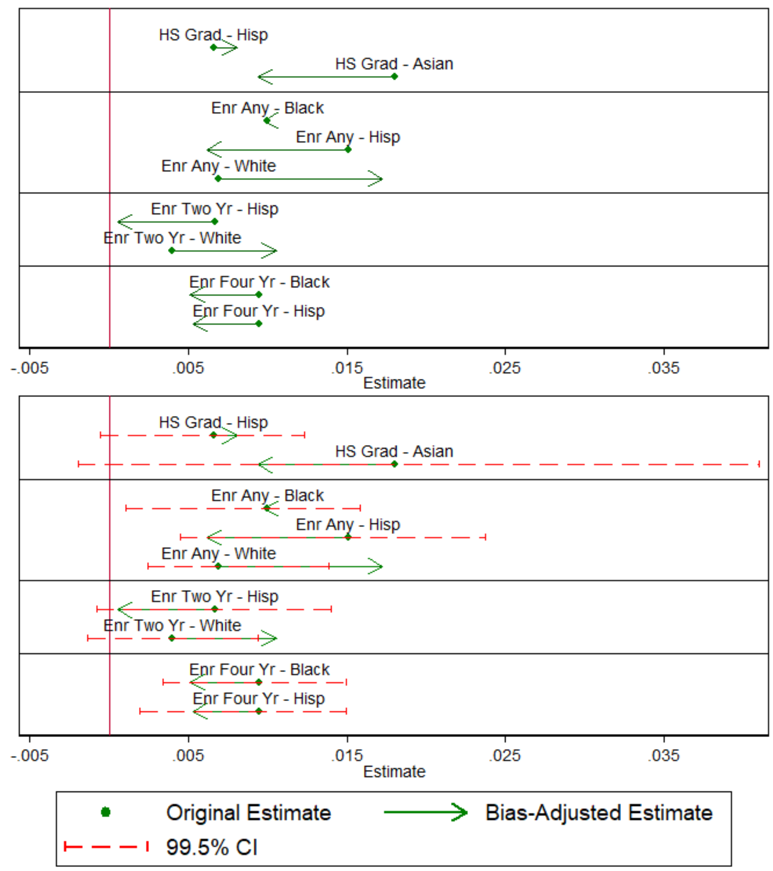
Note: These plots show the non-linear race match effects for two- versus four-year college enrollment. The top left quadrant shows the non-linear effects for Black students, the top right quadrant shows the effects for Hispanic students, the bottom left quadrant shows the effects for Asian students, and the bottom right quadrant shows the effects for White students. For context, I include the histogram for race-matches for each race in the plot to determine how the support for each plot varies by race. The left y-axis scales the effect size and the right y-axis scales the histogram. The group for no race matches is omitted as the reference group. The coefficients are displayed in Table 7. Standard errors are clustered at the school level.

Figure 8: Bounding Sets and Robustness for Short-term Results



Note: These figures plot the bounding set for significant estimates on race-matching for short-term outcomes. The arrow indicates the direction of the bais and how different the bias adjusted estimate is from the original estimate. The first figure tests if the bounding set includes zero which is shown using a red line. The second figure tests if the bounding set is within the 99.5% confidence interval of the original estimate, denoted using dashed red lines.

Figure 9: Bounding Sets and Robustness for Long-term Results



Note: These figures plot the bounding set for significant estimates on race-matching for long-term outcomes. The arrow indicates the direction of the bais and how different the bias adjusted estimate is from the original estimate. The first figure tests if the bounding set includes zero which is shown using a red line. The second figure tests if the bounding set is within the 99.5% confidence interval of the original estimate, denoted using dashed red lines.

Appendix A. Placeholder

Table A1: Black Student to Black Teacher Sorting

VARIABLES	(1) Black Teacher	(2) Black Teacher	(3) Black Teacher	(4) Black Teacher
Black Student	0.152***	0.00801***	0.00797***	0.00376***
	(0.0117)	(0.000747)	(0.000745)	(0.000468)
HS FE		X	X	X
HS, Year FE			X	X
HS by Year by Course FE				X
Observations	8,960,036	8,960,036	8,960,036	8,958,612
R-squared	0.039	0.232	0.232	0.620

Table gives the regressions estimated separately using varying fixed effects to estimate the likelihood that Black students and Black teachers are matched. Standard errors are clustered at the school level.

Table A2: Hispanic Student to Hispanic Teacher Sorting

VARIABLES	(1) Hispanic Teacher	(2) Hispanic Teacher	(3) Hispanic Teacher	(4) Hispanic Teacher
Hispanic Student	0.218***	0.00291***	0.00281***	0.00122***
	(0.0143)	(0.000430)	(0.000428)	(0.000294)
HS FE		X	X	X
HS, Year FE			X	X
HS by Year by Course FE				X
Observations	8,960,036	8,960,036	8,960,036	8,958,612
R-squared	0.039	0.232	0.232	0.620

Table gives the regressions estimated separately using varying fixed effects to estimate the likelihood that Hispanic students and Hispanic teachers are matched. Standard errors are clustered at the school level.

Table A3: Asian Student to Asian Teacher Sorting

VARIABLES	(1) Asian Teacher	(2) Asian Teacher	(3) Asian Teacher	(4) Asian Teacher
Asian Student	0.0266***	0.00361***	0.00360***	0.00144**
	(0.00343)	(0.00109)	(0.00109)	(0.000675)
HS FE		X	X	X
HS, Year FE			X	X
HS by Year by Course FE				X
Observations	8,960,036	8,960,036	8,960,036	8,958,612
R-squared	0.039	0.232	0.232	0.620

Table gives the regressions estimated separately using varying fixed effects to estimate the likelihood that Asian students and Asian teachers are matched. Standard errors are clustered at the school level.

Table A4: White Student to White Teacher Sorting

VARIABLES	(1) White Teacher	(2) White Teacher	(3) White Teacher	(4) White Teacher
White Student	0.261***	0.00455***	0.00437***	0.00193***
	(0.0126)	(0.000589)	(0.000587)	(0.000368)
HS FE		X	X	X
HS, Year FE			X	X
HS by Year by Course FE				X
Observations	8,960,036	8,960,036	8,960,036	8,958,612
R-squared	0.039	0.232	0.232	0.620

Table gives the regressions estimated separately using varying fixed effects to estimate the likelihood that White students and White teachers are matched. Standard errors are clustered at the school level.

Table A5: Covariates of Black Students that Predict Black Teachers

VARIABLES	(1) Black Teacher	(2) Black Teacher	(3) Black Teacher	(4) Black Teacher
Gifted	0.0381***	-0.0151***	-0.0150***	-0.00586**
	(0.0101)	(0.00291)	(0.00290)	(0.00232)
Free/Reduced Lunch	0.0531***	0.00190**	0.00179**	0.00105*
	(0.00689)	(0.000814)	(0.000807)	(0.000595)
8th Grade Reading Z-Score	0.00880***	0.00283***	0.00263**	-0.00133**
	(0.00250)	(0.00104)	(0.00104)	(0.000598)
8th Grade Math Z-Score	-0.00662***	0.00460***	0.00475***	0.00244***
	(0.00254)	(0.000801)	(0.000825)	(0.000625)
HS FE		X	X	X
HS, Year FE			X	X
HS by Year by Course FE				X
Observations	1,130,802	1,130,781	1,130,781	1,104,843
R-squared	0.013	0.280	0.280	0.654

Table give regressions estimated separately using varying fixed effects to estimate what covariates of Black students predict having Black teachers matching along racial lines. Regressions are limited to Black students. Standard errors are clustered at the school level.

Table A6: Covariates of Hispanic Students that Predict Hispanic Teachers

VARIABLES	(1) Hispanic Teacher	(2) Hispanic Teacher	(3) Hispanic Teacher	(4) Hispanic Teacher
Gifted	0.100***	-0.00901***	-0.00888***	-0.00362***
	(0.0129)	(0.00136)	(0.00136)	(0.000999)
Free/Reduced Lunch	0.0926***	0.00243***	0.00244***	0.00153***
	(0.0121)	(0.000588)	(0.000588)	(0.000395)
8th Grade Reading Z-Score	-0.0316***	-0.00246***	-0.00318***	-0.00140***
	(0.00409)	(0.000675)	(0.000673)	(0.000414)
8th Grade Math Z-Score	0.0335***	-0.000222	0.000103	-0.000410
	(0.00515)	(0.000649)	(0.000651)	(0.000405)
HS FE		X	X	X
HS, Year FE			X	X
HS by Year by Course FE				X
Observations	4,415,867	4,415,856	4,415,856	4,400,327
R-squared	0.017	0.461	0.461	0.732

This table gives regressions estimated separately using varying fixed effects to estimate what covariates of Hispanic students predict having Hispanic teachers matching along racial lines. Regressions are limited to Hispanic students. Standard errors are clustered at the school level.

Table A7: Covariates of Asian Students that Predict Asian Teachers

VARIABLES	(1) Asian Teacher	(2) Asian Teacher	(3) Asian Teacher	(4) Asian Teacher
Gifted	0.00869	0.00135	0.00174	0.000104
	(0.00673)	(0.00287)	(0.00290)	(0.00142)
Free/Reduced Lunch	0.00525	-0.000954	-0.00106	-0.00121*
	(0.00358)	(0.000851)	(0.000843)	(0.000702)
8th Grade Reading Z-Score	-0.00210	-0.00110	-0.00265**	-0.00167**
	(0.00144)	(0.000983)	(0.00110)	(0.000793)
8th Grade Math Z-Score	0.000142	-0.00119	-0.000311	0.000430
	(0.00191)	(0.000995)	(0.00109)	(0.000647)
HS FE		X	X	X
HS, Year FE			X	X
HS by Year by Course FE				X
Observations	400,796	400,785	400,785	379,993
R-squared	0.001	0.062	0.062	0.579

This table gives regressions estimated separately using varying fixed effects to estimate what covariates of Asian students predict having Asian teachers matching along racial lines. Regressions are limited to Asian students. Standard errors are clustered at the school level.

Table A8: Covariates of White Students that Predict White Teachers

VARIABLES	(1) White Teacher	(2) White Teacher	(3) White Teacher	(4) White Teacher
Gifted	-0.0112***	0.0105***	0.0102***	0.00525***
	(0.00363)	(0.00131)	(0.00130)	(0.00103)
Free/Reduced Lunch	-0.0163***	-0.00363***	-0.00356***	-0.00145***
	(0.00280)	(0.000565)	(0.000564)	(0.000398)
8th Grade Reading Z-Score	-0.00439***	-0.00114*	0.000206	0.00118***
	(0.00116)	(0.000615)	(0.000605)	(0.000423)
8th Grade Math Z-Score	0.00674***	-0.000385	-0.000998*	-0.000623
	(0.00156)	(0.000568)	(0.000565)	(0.000464)
HS FE		X	X	X
HS, Year FE			X	X
HS by Year by Course FE				X
Observations	2,965,012	2,964,999	2,964,999	2,949,041
R-squared	0.002	0.129	0.129	0.562

This table gives regressions estimated separately using varying fixed effects to estimate what covariates of White students predict having White teachers matching along racial lines. Regressions are limited to White students. Standard errors are clustered at the school level.

Table A9: Dosage – Black Student to Black Teacher Sorting

VARIABLES	(1) Black Teacher	(2) Black Teacher	(3) Black Teacher	(4) Black Teacher
Black Student	0.669***	0.0239***	0.0133***	0.0142***
	(0.0557)	(0.00447)	(0.00309)	(0.00306)
HS FE		X	X	X
Course Set			X	X
Cohort Course Set				X
Observations	562,255	562,246	514,501	506,034
R-squared	0.091	0.627	0.749	0.773

Table gives the regressions estimated separately using varying fixed effects to estimate the likelihood that Black students and Black teachers are matched. Standard errors are clustered at the school level.

Table A10: Dosage – Hispanic Student to Hispanic Teacher Sorting

VARIABLES	(1) Hispanic Teacher	(2) Hispanic Teacher	(3) Hispanic Teacher	(4) Hispanic Teacher
Hispanic Student	0.973***	0.0119***	0.00619***	0.00547**
	(0.0638)	(0.00331)	(0.00237)	(0.00231)
HS FE		X	X	X
Course Set			X	X
Cohort Course Set				X
Observations	562,255	562,246	514,501	506,034
R-squared	0.172	0.801	0.876	0.889

Table gives the regressions estimated separately using varying fixed effects to estimate the likelihood that Hispanic students and Hispanic teachers are matched. Standard errors are clustered at the school level.

Table A11: Dosage – Asian Student to Asian Teacher Sorting

VARIABLES	(1) Asian Teacher	(2) Asian Teacher	(3) Asian Teacher	(4) Asian Teacher
Asian Student	0.0905***	0.0166***	0.00917***	0.00798**
	(0.0143)	(0.00532)	(0.00336)	(0.00334)
HS FE		X	X	X
Course Set			X	X
Cohort Course Set				X
Observations	562,255	562,246	514,501	506,034
R-squared	0.009	0.279	0.472	0.518

Table gives the regressions estimated separately using varying fixed effects to estimate the likelihood that Asian students and Asian teachers are matched. Standard errors are clustered at the school level.

Table A12: Dosage – White Student to White Teacher Sorting

VARIABLES	(1) White Teacher	(2) White Teacher	(3) White Teacher	(4) White Teacher
White Student	1.144***	0.0403***	0.00895***	0.00763***
	(0.0524)	(0.00492)	(0.00286)	(0.00283)
HS FE		X	X	X
Course Set			X	X
Cohort Course Set				X
Observations	562,255	562,246	514,501	506,034
R-squared	0.171	0.668	0.835	0.851

Table gives the regressions estimated separately using varying fixed effects to estimate the likelihood that White students and White teachers are matched. Standard errors are clustered at the school level.

Table A13: Dosage – Covariates of Black Students that Predict Black Teachers

VARIABLES	(1) Black Teacher	(2) Black Teacher	(3) Black Teacher	(4) Black Teacher
Gifted	0.198***	-0.0415*	0.00584	0.00616
	(0.0565)	(0.0241)	(0.0164)	(0.0154)
Free/Reduced Lunch	0.293***	0.0163***	0.00909*	0.00611
	(0.0377)	(0.00591)	(0.00552)	(0.00563)
8th Grade Reading Z-Score	0.0255*	-0.0115	0.00118	-0.00104
	(0.0150)	(0.00752)	(0.00621)	(0.00621)
8th Grade Math Z-Score	-0.0282**	0.0144**	0.00178	0.000954
	(0.0134)	(0.00681)	(0.00643)	(0.00610)
HS FE		X	X	X
Course Set			X	X
Cohort Course Set				X
Observations	73,062	72,910	59,580	57,117
R-squared	0.033	0.680	0.797	0.819

Regressions estimated separately using varying fixed effects to estimate what covariates of Black students predict having Black teachers matching along racial lines. Regressions are limited to Black students. Standard errors are clustered at the school level.

Table A14: Dosage – Covariates of Hispanic Students that Predict Hispanic Teachers

VARIABLES	(1) Hispanic Teacher	(2) Hispanic Teacher	(3) Hispanic Teacher	(4) Hispanic Teacher
Gifted	0.510***	-0.0172	-0.00639	-0.00808
	(0.0659)	(0.0130)	(0.00789)	(0.00776)
Free/Reduced Lunch	0.418***	0.00818*	0.00724**	0.00634*
	(0.0538)	(0.00431)	(0.00362)	(0.00351)
8th Grade Reading Z-Score	-0.163***	-0.0376***	0.00445	-0.00298
	(0.0204)	(0.00673)	(0.00557)	(0.00396)
8th Grade Math Z-Score	0.144***	-0.0132**	-0.00381	0.00189
	(0.0250)	(0.00633)	(0.00626)	(0.00414)
HS FE		X	X	X
Course Set			X	X
Cohort Course Set				X
Observations	270,465	270,429	238,125	232,276
R-squared	0.028	0.807	0.889	0.901

Regressions estimated separately using varying fixed effects to estimate what covariates of Hispanic students predict having Hispanic teachers matching along racial lines. Regressions are limited to Hispanic students. Standard errors are clustered at the school level.

Table A15: Dosage – Covariates of Asian Students that Predict Asian Teachers

VARIABLES	(1) Asian Teacher	(2) Asian Teacher	(3) Asian Teacher	(4) Asian Teacher
Gifted	0.0237	-0.00197	0.00646	0.00480
	(0.0331)	(0.0160)	(0.0111)	(0.0127)
Free/Reduced Lunch	0.00669	-0.0135*	-0.0140**	-0.0121*
	(0.0150)	(0.00737)	(0.00652)	(0.00700)
8th Grade Reading Z-Score	-0.00579	0.000577	0.00918	0.00140
	(0.00866)	(0.00815)	(0.0101)	(0.00854)
8th Grade Math Z-Score	0.00538	-0.00528	0.000744	0.000631
	(0.0119)	(0.00987)	(0.00896)	(0.00778)
HS FE		X	X	X
Course Set			X	X
Cohort Course Set				X
Observations	24,274	24,069	18,534	17,438
R-squared	0.001	0.329	0.564	0.616

Regressions estimated separately using varying fixed effects to estimate what covariates of Asian students predict having Asian teachers matching along racial lines. Regressions are limited to Asian students. Standard errors are clustered at the school level.

Table A16: Dosage – Covariates of White Students that Predict White Teachers

VARIABLES	(1) White Teacher	(2) White Teacher	(3) White Teacher	(4) White Teacher
Gifted	-0.0391*	0.0481***	0.0186**	0.0207**
	(0.0227)	(0.0129)	(0.00842)	(0.00832)
Free/Reduced Lunch	0.0179	-0.0182***	-0.00265	-0.00283
	(0.0169)	(0.00590)	(0.00379)	(0.00356)
8th Grade Reading Z-Score	-0.0589***	-0.0442***	-0.000535	0.0111***
	(0.00885)	(0.00697)	(0.00647)	(0.00410)
8th Grade Math Z-Score	0.00843	-0.0295***	0.00699	-0.000560
	(0.0110)	(0.00661)	(0.00625)	(0.00383)
HS FE		X	X	X
Course Set			X	X
Cohort Course Set				X
Observations	191,190	191,115	168,195	163,583
R-squared	0.003	0.427	0.779	0.801

Regressions estimated separately using varying fixed effects to estimate what covariates of White students predict having White teachers matching along racial lines. Regressions are limited to White students. Standard errors are clustered at the school level.