Heterogeneous Impact of Teacher-Student Demographic Mismatch on Math and Science Achievement

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Abstract

This paper focuses on the impact of teacher-student demographic mismatch on student success in 9th grade in U.S. high schools. In this paper, using data from the High School Longitudinal Survey of 2009 (HSLS:09), I investigate whether being assigned to a teacher of different sex and/or different race has significant negative impact on student achievement. HSLS:09 is the only nationally representative high school-level survey data that matches math and science teachers to students and student performance. I create a student-level short-panel dataset to find the effect of demographic mismatch in class on math and science class performance. The results show that having a different-sex teacher is disadvantageous for students of almost all racial backgrounds. Having a different-sex and different-race teacher is associated with achievement loss, especially for Black female students (0.3 standard deviations). Furthermore, the impact of demographic mismatch tends to be concentrated on Black students attending schools with less racial diversity.

JEL Codes: I21, I24, J15

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1 Introduction

This paper examines the impact of demographic mismatches between math and science teachers and 9th-grade students in U.S. high schools. A demographic mismatch is defined here as a student being assigned to a teacher of a different sex and/or race. The principal focus of the study is to identify how these mismatches affect student achievement, with a special emphasis on the achievement of minority students. The motivation for this study is largely driven by the significance of the racial gap in STEM (Science, Technology, Engineering, and Mathematics) achievement in the U.S.

Math and science education at the high school level is foundational for college-level specialization in STEM (Science, Technology, Engineering, and Mathematics) fields[2]. Understanding the drivers of early student success in high school STEM courses is crucial, as majoring or minoring in STEM fields at the undergraduate and graduate levels can significantly shape individuals' career paths and lifetime earnings (Deming and Noray, 2018; Deming and Noray, 2020; Winters, 2014 for review). Furthermore, labor market outcomes are intricately linked to educational experiences and achievements at both pre-college and college levels through various pathways (Altonji, 1992; Loury and Garman, 1995).

Pre-college academic success is influenced by a myriad of factors, including teacher effectiveness, peer-to-peer teaching, teaching practices, school curriculum, classroom size, and the matching or mismatching of teachers' and students' demographic identities, among others (see Lavy, 2016; Kimbrough et al., 2017; Sansone, 2017; Hanushek, 1999). The motivational input from teachers has been recognized as a crucial factor positively influencing student achievement in pre-college education (Feldman, 1988). A segment of economic literature has explored how students might view same-race and same-gender teachers as role models, thereby feeling motivated to improve their academic outcomes (see Dee, 2004 and Ehrenberg and Brewer, 1995, among others). Economists suggest that one of the mechanisms through which race-matching operates is the 'role-model' effect. This effect entails the positive in-

[2]STEM is meant to express a multidisciplinary curriculum focused on scientific fields according to "Digest of Education Statistics. Pocket Digest" (n.d.).

fluence that a minority teacher can have on students from low-income backgrounds and/or minority communities, potentially increasing their effort, confidence, and enthusiasm in class (King, 1993; Cizek, 1995). Conversely, the Golem effect, which can detrimentally impact student achievement, is the opposite of the 'role-model' or Pygmalion effect[3]. The reasons why pedagogy under racial matching improves student outcomes remain a subject of debate, but common life experiences and cultural backgrounds are often credited. Additionally, some studies suggest that same-race and same-gender teachers can serve as role models for racial minority and female students (Dee, 2005; Gershenson et al., 2018; Hoffmann and Oreopoulos, 2009).

In this paper, I utilize nationally representative data from the High School Longitudinal Study of 2009 to test whether a demographic mismatch between students and teachers systematically affects student success[4]. The baseline survey encompasses a sample of 9th graders in both public and private schools in the U.S. during the fall of 2009. This survey data includes information about two teachers from each 9th grader's math and science classes. This detail allows the researcher to control for both observable and unobserved factors associated with demographic mismatch and student achievement. To specify, students may have teachers of a different sex, different race, both different race and different sex, or teachers who are the same sex and race as themselves in their science and math classes. By incorporating demographic mismatch as a variable in a student-level panel model and utilizing the *within*-student variation in demographic mismatch and math/science outcomes, the study explores the impact of having a teacher of a different race, or both a different race and sex, as compared to having a teacher of the same sex and race. The panel model examines the effects of demographic mismatch on student achievement, with these variables varying between math and science classes.

This dataset captures the variation in student outcomes as well as the variation in the demographic identities of teachers across different courses. This characteristic enables an examination of the within-student effect of demographic mismatch. Ideally, we would expect a demographic match or mismatch to have no effect on student

[3]The Golem effect refers to the phenomenon where low expectations placed on students by teachers result in lower performance and academic outcomes. For an introduction to the study of the golem effect generated by biased teachers in public schools, please see Babad et al. (1982)

[4]Source: *High School Longitudinal Study of 2009 (HSLS:09/16), Base-year Survey* (2009)

outcomes. However, if within-student differences in teacher demographic identities are systematically related to student outcomes, it would suggest that demographic mismatch is disadvantageous for students who experience it. For the main empirical analysis in this paper, I restructure the data into a panel format, with the student ID as the panel variable. This format allows the student outcome to vary between math and science GPA in the 9th grade. It also permits the demographic mismatch to vary between the two courses. Any variation in GPA between science and math due to differences in demographic match or mismatch can be analyzed using a student-specific panel model. This model also controls for student-specific observed and unobserved effects with student fixed effects. This identification strategy has been employed by Dee (2004), Gershenson et al. (2016), Fairlie et al. (2014), and many others. The primary variable for student achievement in this paper is the 9th-grade math and science GPA, z-scored at the school level.

Dee (2004) and Gershenson et al. (2016) examine teachers' expectations as an outcome variable in their research. Expectations are inherently noisy. If this noise is not random and is systematically connected to the main explanatory variables, the estimated results could be biased (Mullainathan and Bertrand, 2001). If a teacher consistently exhibits bias, then a teacher fixed-effect model may at least mitigate the issue of expectation-driven outcomes being noisy. In contrast to these authors, I focus solely on student outcomes that are measured and published by schools. GPA is objectively measured and does not contain measurement error problems like the subjective measures of teachers' expectations. The 9th-grade GPA data is sourced from student certificates collected and organized by HSLS:09. I compile this grade data for the sampled students and calculate their GPA using the formula published by HSLS:09[5]. Additionally, I test for possible selection bias arising from merit-based placement in math and science classes. However, I find no evidence that students on average received merit-based placement in 9th-grade classes. Moreover, in the 9th grade, students are typically offered required and/or foundational courses in math and science, which limits their course selection and reduces self-selection into these

[5]The 9th-grade GPA is calculated using course-specific information from a restricted-access file provided by the IES. Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

courses. If not corrected or adjusted for, selection bias could render the estimated coefficients of demographic mismatch biased and invalid.

The primary contribution of this paper is its demonstration, using nationally representative data of 9th graders, that teacher-student demographic mismatch in the classroom can negatively affect objectively measurable student outcomes, like standardized GPA in STEM courses. Secondly, this paper expands our understanding of the impact of demographic mismatch on student outcomes by accounting for multiple sources of heterogeneity in the mismatch effect across courses and within a school. Furthermore, the paper presents robust and consistent evidence of a negative effect on 9th-grade STEM GPA when a student is assigned to a different-sex teacher. The evidence of a negative effect from having a different-race teacher is particularly notable among Asian students and Black female students. This finding is significant for policymakers, considering the well-documented racial gap in educational attainment (Ferguson, 2003; Arcidiacono et al., 2012; Fryer Jr. and Katz, 2013). There are three categories of demographic mismatch discussed in this paper: different sex and different race, different race and same sex, and different sex and same race. For instance, if a teacher is Asian and the student is Black, and both are female, then 'different race and same sex = 1' applies. 'Same sex and same race' is used as the reference category, against which the effects of demographic mismatch are measured. Having a same-sex and same-race teacher could be a source of a role model or Pygmalion effect, potentially generating positive impacts on student outcomes. Lastly, this paper sheds light on potential channels connecting demographic mismatch and student outcomes.

The estimated negative effect of demographic mismatch reflects the Golem effect. This concept hinges on the assumption that students are not assigned to teachers based on their own preferences or the teachers' preferences, as confirmed by sorting tests. However, it is possible that even with random demographic mismatch, its impact on student performance is influenced by the unobserved teacher quality, particularly low-performing non-minority teachers. Moreover, the Golem effect is not objectively measurable, especially if course outcomes such as GPA or letter grades lack objective measurements. Further, the demographic mismatch in the data I utilize is not the result of controlled randomized assignment. Therefore, the results presented in this paper are intended to demonstrate the negative association between demographic mismatch and math/science outcomes, which may, at least partially, be attributed to the Golem effect. I also explore additional channels through which demographic mismatch may operate by plausibly increasing the need for minority students to have teachers of the same race and gender.

The analysis indicates that factors such as lower average student abilities, student unpreparedness being a problem for the school, and overcrowding can act as channels through which demographic mismatch might affect student achievement. One particularly notable channel in the analysis is the racial diversity of schools. Black students seem to experience the negative effects of demographic mismatch more acutely in schools with less racial diversity. The lack of racial diversity may intensify the students' perception of being a minority and the need for teachers of the same demographic background, who could serve as role models.

This paper proceeds as follows: Section 2 briefly discusses some relevant theoretical and empirical works on the channel of demographic match and mismatch. Section 3 discusses the data. Section 4 describes the main model. Section 5 discusses necessary tests for the validity of the model parameters of interest. Section 6 discusses empirical results and Section 7 concludes.

2 Literature Review

Teachers influence student outcomes in many ways. Their expectations, encouragement, persistence, and motivation, which can broadly be defined as subjective inputs, may correlate with the demographic identities of both the teacher and his or her students. Heightened teacher expectations can become self-fulfilling for students. This phenomenon, known as the 'Pygmalion effect,' has been extensively studied and experimented with. Rosenthal (1968) conducted a field experiment in a U.S. public elementary school and found that heightened teacher expectations were associated with faster IQ gains. Similarly, Eden and Shani (1982) replicated this experiment with members of the Israeli Defense Forces and concluded that leadership behavior was a key mediator in generating the Pygmalion effect. Conversely, the self-fulfilling nature of lowering expectations is known as the 'Golem effect' (Reynolds, 2007). An instance of the Golem effect was observed by Rist (1970), who demonstrated that teachers' perceptions, influenced by the social class of students, played a role in determining student outcomes. He provided evidence that teachers' initial negative beliefs about students from disadvantaged social classes corresponded with lower levels of student achievement.

The role of self-fulfilling prophecies in enhancing student outcomes has been explored by numerous authors. If teachers have high expectations for their students, and in turn, these students, aware of their teachers' expectations, increase their effort to succeed, then teachers' expectations are effectively creating self-fulfilling prophecies (Brophy, 1983; Jussim and Harber, 2005; Jussim and Eccles, 1992). Some experts have found that the test score gap between White and African American students is perpetuated by teacher perceptions (Ferguson, 2003 and others). Ehrenberg and Brewer (1995) reveals that instruction from an African American teacher was associated with higher gains in scores for African American high school students.

The existing body of literature demonstrates that a teacher's motivational input can influence not only a student's achievement within a specific class but also enhance the student's drive to accomplish future academic goals (Spera and Wentzel, 2003). Teachers evaluate their students' work and can make them aware of their mistakes, give valuable suggestions, and praise them for their successes. These inputs can reinforce a student's confidence in a class and motivate them to work harder in the future (Turner et al., 2002; Urdan and Schoenfelder, 2010). The challenges students face in class, such as disruptions and peer abilities, can be mitigated by teachers' appreciation and encouragement (Bandura, 1986; Dweck and Leggett, 1988). Beyond instructional motivation, designing classes to increase student autonomy can effectively boost student performance (Stefanou et al., 2013). Although teachers' subjective motivational inputs are assumed to have a direct relation with student outcomes, the education literature pays little attention to identifying specific channels of interaction between them. The self-fulfilling prophecy is one channel that economic theory posits as responsible for this interaction[6]. The channel of the Role-model effect, discussed in section 1, functions similarly in creating self-fulfilling prophecies. More recently, evidence of the Golem effect, or the opposite of the Pygmalion effect, has been found in Dee (2004, 2005), Fairlie et al. (2014), Gershenson et al. (2016), and Sansone (2017). The Golem effect, in the case of demographic mismatch, is associated with negative student outcomes or adverse effects on student achievement.

3 The Data

In this section, I discuss the data used in the study and discuss descriptive statistics based on the data. Section 3.1 discusses the data source and Section 3.2 discusses the statistical description of some of the key variables that are later used in the empirical analysis of the paper.

3.1 High School Longitudinal Study of 2009 (HSLS:09)

The data used in this paper is sourced from the High School Longitudinal Study of 2009 (HSLS:09)[7], a nationally representative survey sponsored by the U.S. Department of Education. This survey follows a single cohort of U.S. high school students, initially consisting of 9th graders in the fall of 2009[8]. The base year survey was conducted in 2009, and the data from this survey are utilized in this paper. The data files covering the teacher survey, high-school administrator or principal survey, high-school counselor survey, and the student survey are included. The 9th-grade science and math GPAs have been calculated using the restricted-access student-course file in HSLS:09. These student-course files contain all the course information of the respondent students[9]

[6]In recent economic literature, subjective measures of student and teacher quality have been widely used. Some studies estimating the effect of subjective evaluation scores of teachers on student achievement use evaluations from professional agencies specializing in training, mentoring, and rating teachers' effectiveness (Rockoff and Speroni, 2010; Kane et al., 2011; Bacher-Hicks et al., 2017; Blazar, 2015; Kane and Staiger, 2008; Kane and Staiger, 2012).

[7]Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

[8]Schools and Students are the data sampling units, not parents; the response rates are in terms of schools and students.

[9]The high schools that participated in HSLS:09 provided the course information directly. I calculated the grade points for 9th-grade math and science using the same categorization used to create high school

The HSLS:09 contains detailed information about students' academic achievements, socioeconomic backgrounds, demographic characteristics, educational attainment of parents, parents' occupations, etc. The survey collects data on the home life and background information of parents, administrators (principals), and high school counselors. In the sampled schools, math and science teachers also participated in the survey through a separate questionnaire[10]. HSLS:09 employed a stratified, two-stage random sample design, with primary sampling units defined as schools in the first stage, and students were randomly selected from the sampled schools in the second stage. The target population of HSLS:09 was defined as students from 944 public schools, including public charter schools, and private schools in the 50 states and the District of Columbia that provided instruction to 9th-grade students in Fall 2009. Ingles et al. (2011) and Duprey et al. (2018) provide detailed information on school inclusion and exclusion rules. They also discuss further details about survey administration and sample selection. A sample of 25,210 study-eligible students was retained in the published data.

I have created an unbalanced panel of distinct 9th-grade students, each with two observations for math and science. 82% of the students have two observations, while 18% have only one. This imbalance is primarily due to non-response from their math and science teachers. The total number of student-teacher observations in the unbalanced panel is 16,730[11]. All unweighted sample sizes are rounded off to tens, as per IES regulation. In HSLS:09, students were asked to provide infor-

math and science GPA in the publicly-available 'school course' files (X3TGPAMTH and X3TGPASCI, respectively). The course-specific grade point information for Fall 2009 comes from restricted-access 'school course' files supplied by IES directly. Grade point calculation is specific to the 9th-grade class of a school. The course file lists additional categorizations such as 'pass' and 'fail' as course outcomes. Using the same categorization, I assign the median grade of the sample of the 9th-grade class of a specific school to the 'pass' category and 0 to the 'fail' category. For students who took multiple math and/or science courses in Fall 2009, the math and science grade points are calculated as averages of the grade points they received in those courses that semester. Source: **U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."**.

[10] The published data links teachers, parents, administrators, and high school counselors to students. In the teacher questionnaire, teachers were asked questions about their qualifications, experience, and the student body. An individual student is matched to his/her math or science teacher in Fall 2009. If a student was taking multiple math/science classes, the student is matched to one of the teachers from those classes.

[11] The math teacher survey data had over 6,430 missing responses, science teacher survey data had 7,940, and principal survey data had about 1,500. The Parent survey in HSLS:09 has an additional 6,500 missing observations. Parent survey variables are not necessary to be included in the analytical sample as they are invariant within a student.

mation about their teachers during the student survey. Subsequently, teachers were contacted and invited to participate in the survey. The student survey file has a cross-sectional layout where the teacher responses and principal responses (columns) are identified with student and school IDs in each row. HSLS:09 does not include unique IDs for teachers, but grouping some teacher responses for each school allowed for the creation of unique teacher ID variables[12]. These teacher response variables include race, sex, highest degree earned, year of highest degree earned, whether their highest degree is in a STEM field, whether the math teacher's BA/BS degree was awarded by the education department, the type of teaching certificate currently held, years of experience teaching 9th to 12th grade, and whether the teacher was contributing to a teacher retirement system/401(k)/403(b). For my analysis, identifying unique teachers is not necessary, but it is used for a sensitivity analysis. Unique teacher identifiers are based on school IDs and unique combinations of answers to survey questions. School *times* unique teacher fixed effects control for the varied effects within each school that different math/science teachers may have on student achievement.

3.2 Key Instruments of Analytical Sample

The HSLS:09 contains detailed information about students. The main analysis in this paper uses a panel of 9th-grade students and their math and science teachers' response variables. The primary outcome variable, 9th-grade GPA, varies within math and science courses, as do the explanatory variables. Every observation is unique at the Student$\times$course level, with Student ID as the panel variable. Table 1 presents a statistical description of the key outcome variables and some other measures of student achievement. In Table 1, Columns 3, 4, and 6 refer to mean-difference t-tests between Column 2 (White Students) and Columns 3 (Non-white Students), 4 (Black students), and 5 (Male Students) and 6 (Female students), respectively. The stars signify the p-values of the t-test statistic[13]. Table 1 shows that the mean STEM GPA (9th grade) is significantly different between White and Non-white students,

[12]Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

[13]The stars or asterisks ***, **, * refer to ***$p<0.01$, **$p<0.05$, and *$p<0.1$ of the statistic of the mean-difference t-tests.

as well as between White and Black students[14]. The mean GPA for White students is higher than that of Non-white and Black students. Conversely, the mean GPA for female students is significantly higher than that of male students, indicating a gender gap reversal in education (Hershbein, 2013). This pattern of demographic differences in achievement holds true for other student outcomes, such as math/-science AP credits in high school, high school math/science GPA, and self-efficacy in math/science[15]. Minority students - Non-white and Black - on average face more teachers of a different race, encounter a smaller number of certified teachers, and slightly fewer teachers with STEM degrees.

Table 2 presents the means of the same variables as Table 1, but for samples split by teacher types. Black and non-White teachers face smaller average 9th-grade GPAs among the students they teach. This finding aligns with the economic literature, which indicates that white teachers are more likely to teach in higher-performing schools and that Black teachers tend to move to schools with a higher percentage of Black students (Hanushek et al., 2004)[16]. Female teachers, on average, have fewer STEM degrees and less experience, as shown in Table 2. However, according to Table 1, female students have higher levels of achievement, except in self-efficacy. Family income and parents' education are two major drivers of student achievement. Since these factors are invariant within a student, they are not included in the panel analysis[17]. Nonetheless, it is interesting to note how these two variables vary across races. The mean (annual) family income corresponding to the White student sample is approximately 20 thousand dollars higher than that in the non-White sample and even higher than in the Black sample (Table A.2). Overall, the sample means for White teachers and White students resemble the total sample

[14]GPA is measured on a standard 4-point scale.

[15]Self-efficacy is a standardized variable that presents the scale of the student's efficacy in math or science. This variable is provided in HSLS:09 and is created through principal components factor analysis. The inputs to this scale were variables that rated (1) how prepared the student feels about the math/science tests, (2) how well the student understands the math/science textbooks, (3) how confident the student is about his/her skills in math/science, and (4) how confident the student is that she/he would excel in the math/science course on a Likert scale.

[16]Black teachers, on average, are assigned to students of a different sex and different race in a sample of multiple schools across different school districts, even when school and higher-order heterogeneity are controlled for (Hanushek et al., 2004).

[17]Furthermore, variables from the parent survey in HSLS:09 suffer from a high degree of missing responses. The variables for family income and parents' education are both derived from various responses in the parent survey.

means of the variables. White students stand out as having higher levels of average student achievement compared to non-White and Black students, a phenomenon often noted in education research (Arcidiacono et al., 2012; Fryer Jr. and Katz, 2013, and others).

4 Model

The main model for this paper is an "Education Production Function" (Krueger, 1999)[18]. Class size is input in his education production function. The basic structure of the education production function shows the relationship between outcome Y_{ij} and inputs such as indicators of demographic mismatch, achievement controls, etc.

$$Y_{ij} = f(D_{ij}, \mathbf{X}, \epsilon_{ij}) \text{ where } j \in \{S, M\} \tag{1}$$

In the equation 1, S stands for Science and M for Math. The above equation shows that student achievement y_i is a function of educational inputs for student i in a sample of N students. ϵ_{ij} is an error vector with a normal distribution. D_{ij} is the vector of the demographic mismatch indicators.

Formally, the STEM achievement is modeled as equation 2. This is a panel model where the outcome and explanatory variables vary across the courses and within each student. Student-specific effects - both unobserved and observed, and invariant *within* each student - on the outcome are thus controlled for. This identification strategy was first implemented by Dee (2005) and others.

$$Y_{ij} = \alpha_j + \gamma_i + \mathbf{X}'_{ij}\beta + \mathbf{D}'_{ij}\Omega + \epsilon_{ij} \;\; \forall \; j \in \{S, M\} \tag{2}$$

In equation 2, α represents a subject fixed effect (either math or science) that controls for systemic differences in these two courses. γ is a student fixed effect that controls for unobserved student characteristics. In a pooled model without γ, or where data is available for only one course, γ would be included in the error term,

[18] In Krueger (1999), Education production function models student achievement (SAT score of the students in Tennessee STAR school) – on independent variables such as student characteristics, class size, etc. He tests the hypothesis that smaller class size would increase student achievement.

making the estimate of Ω biased. Math and science skills overlap in certain ways, e.g., mathematical computation is necessary in geometry, algebra, and physics. Due to this overlap in skills, γ captures a greater degree of unobserved effects than it would in a model where achievement varies between reading or writing and math courses. Ω captures the effect of demographic mismatch (race and gender mismatch) compared to race and gender matching between the teacher and the student. D_{ij} is a vector of three categorical variables representing the student having a (1) different-race and same-sex teacher, (2) different-sex and same-race teacher, or (3) different-sex and different-race teacher. The reference category for these variables, indicating 'Yes' (1), is having a same-race and same-sex teacher.

D_{ij} represents a vector of four mutually exclusive categories of teacher-student demographic mismatch. The best strategy for categorizing demographic mismatch is using same-race-same-sex as the reference category, as the expected signs of all other categories would be negative. If other-race-other-sex were the reference, then 'same race but other sex' could have either sign because same race is an improvement on the reference category, but other sex is not. A negative sign could reflect the 'other' neutralizing the 'same'. The effect of demographic mismatch or matching between teachers and students is likely to be more pronounced for minority students. Among the main minority groups - Black, Hispanic, and Asian - Black and Hispanic students have a relatively higher percentage of racial match with their teachers, approximately 5%. However, only 1.5% of Asian students see the least percentage of racial matches with their teachers. Therefore, in this paper, the main focus is on the demographic mismatch impact for Black students.

Across minority races, the effect of demographic mismatch can vary, making it heterogeneous. Thus, I split the analytical samples into demographic categories to observe the differences in the effect of demographic mismatch. The main outcome variable is z-scored, as the main explanatory variables - D_{ij} - cause differences in the average position of the students in their class. As the model has a within-student panel structure, the estimated effect of D_{ij} is driven by variations in demographic mismatch *between* math and science courses. On average, a demographic mismatch in a math or science class would likely result in a lower position in that class compared to the other class where the student sees a demographic 'match' with the teacher. This setup assumes that the effect of demographic mismatch is the same for both math and science.

5 Sorting Tests

HSLS:09 randomly selected students for the survey, but the teachers were not randomly assigned to them. If student achievement factors into the racial matching between teachers and students, it poses a threat to the validity of the student fixed-effect estimates. For example, if low-performing minority students are more likely to be assigned to classes taught by minority teachers, then the estimated effect of a demographic match between the minority teacher and the student could be biased downward. Conversely, if high-performing students are more likely to be assigned to minority teachers, then the effect of demographic mismatch on student outcomes could be biased upward[19].

$$
\begin{aligned}
NWT_{ijk} = \beta NWS_{ijk} + \eta \textbf{Achievement}_{jk} + \Omega NWS_{ijk} \times \textbf{Achievement}_{jk} + \\
School_k \times Course_j + \epsilon_{ijk} \quad (3) \\
\forall\ j \in \{S, M\}\ \ \&\ \ k = 1, 2, 3..., 944
\end{aligned}
$$

The first test I conduct is similar to the one developed by Lusher et al. (2018). NWT_{ijk} is a binary indicator of a non-White teacher teaching course j in school k to student i. NWS_{ijk} is a binary indicator of a non-White student, using the same subscripts. For $\textbf{Achievement}_{jk}$, I use the teacher-specific average theta score and the standardized grade in the highest math/science course the student took in 8th grade[20]. $School_k \times Course_j$ fixed effects are intended to capture systemic differences in school-specific math and science courses. The main coefficients of interest are β and Ω. If their estimates are statistically significant, the sorting test would indicate

[19] I test for evidence of sorting in this sample using techniques implemented in Fairlie et al. (2014), Gershenson et al. (2016), Lusher et al. (2018), and Oliver et al. (2021).

[20] The mathematical theta score is the score on an algebra test that each respondent took. The score has been z-scored within the sample. More information on the mathematical theta score can be found in Ingels et al. (2011)

that students' racial minority identity is associated with that of the teacher through the student-teacher assignment. Identification of Ω requires multiple teachers for a given school-course combination. Only 93% of the school-courses have more than two unique teachers[21]. Equation 3 is estimated using a pooled OLS model.

The next sorting test, originally developed by Fairlie et al. (2014), checks for differential sorting based on observable characteristics of students. They argue that if there is no sorting based on observed characteristics, and the mean teacher-specific measure of student quality is not correlated with the error in Equation 2, then differential sorting would not threaten the validity of the student fixed-effects estimates in Equation 2. This test examines whether the average quality of students taught by minority teachers is associated with the match between minority teachers and students. For instance, if the average school assigns low-performing minority non-White students to minority teachers, then Ω would be negative and statistically significant. Conversely, if high-performing minority non-White students are assigned to minority teachers, the estimated Ω would be positive. Essentially, Ω estimates how the mean difference in characteristics between White and non-White students varies between White and non-White teachers. If the estimated Ω is statistically indistinguishable from zero, it would suggest that there is no evidence of race-specific sorting based on observable student characteristics, making sorting based on unobserved characteristics of students unlikely. Equation 4 is estimated as a pooled OLS model.

$$\begin{aligned} \overline{Achievement}_{jk} = \beta NWS_{ijk} + \eta NWT_{ijk} + \Omega NWS_{ijk} \times NWT_{ijk} + \\ School_k \times Course_j + \epsilon_{ijk} \\ \forall\ j \in \{S, M\}\ \ \&\ \ k = 1, 2, 3..., 944 \end{aligned} \tag{4}$$

This test examines whether the average quality of students taught by minority teachers is related to the match between minority teachers and their students. For

[21] *High School Longitudinal Study of 2009 (HSLS:09/16), Base-year Survey* (2009) does not provide unique teacher IDs. By identifying unique combinations of teacher responses to various questions (sex, race, years of teaching experience, highest degree, bachelor's degree major, certification type, pension indicator), I create teacher IDs.

instance, if the average school tends to assign low-performing minority non-White students to minority teachers, then Ω would likely have a negative sign and be statistically significant. Conversely, if high-performing minority non-White students are predominantly assigned to minority teachers, then the estimated Ω would be positive. Essentially, Ω assesses how the mean difference in characteristics between White and non-White students varies between White and non-White teachers. If the estimated Ω is statistically indistinguishable from zero, it would indicate that there is no evidence of race-specific sorting based on observable student characteristics, suggesting that sorting based on unobserved student characteristics is also unlikely. Equation 4 is estimated using a pooled OLS model.

6 Results

In this section, the empirical analysis is presented. The sorting tests and other tests are discussed in section 6.1. From section 6.1 to section 6.4, results are primarily derived from pooled regressions. The main model for analysis has a panel structure, as shown in Equation 2. Section 6.5 to section 6.6 discuss the baseline results, robustness tests, and the effect of demographic mismatch on alternative student outcomes.

6.1 Sorting Test Results

The first set of sorting test results are presented in Table 3, showing the estimates of Equation 3. The indicator for non-white students does not have a statistically significant association with the Non-white Teacher indicator (NWT). The interaction terms - Teacher-specific average theta score (MEANTHETA) $\times$ Non-white Student (=1) and Teacher-specific average z-scored grade of the highest math/science course in 8th grade (ZG8) $\times$ Non-white Student (=1) - have coefficient estimates that are statistically indistinguishable from zero.

The second round of sorting test results, based on estimating Equation 4, focuses on the main coefficient of interest, Ω. The estimated results are in Table 4. The interaction term - Non-White Student $\times$ Non-White Teacher - does not have any significant impact on the average MEANTHETA or ZG8. Columns 1 and 2 in

Table 4 are estimated by including School×Course fixed effects, and columns 3 and 4 with only course fixed effects. These results suggest no differential sorting on observed characteristics by student race, implying that differential sorting on unobserved factors is unlikely to threaten the validity of the identification of student fixed effects. Additionally, Table A.5 provides test results of sorting on family income and respondent parents' education. PAR1COL is a binary variable, coded 1 if the respondent parent or parent 1 has a college degree. Across all columns in Table A.5, the interaction term between non-White students and non-White teachers does not produce any significant impact on the observed characteristics - parents' education and family income.

6.2 Falsification Tests

Table 4 results can also be interpreted as results of falsification tests. Rothstein (2010) tested whether present achievement is connected to the teachers to whom students are assigned in the future in a value-added model. If a future teacher's effect on present achievement is found to be statistically significant, it would indicate that the correlation between the input and the outcome is spurious. Following Rothstein (2010), many others have applied different versions of this test with various education production models. Table 4 shows that unique teacher-specific mean ZG8, the z-scored 8th-grade math and science achievement, is not significantly impacted by the Non-white student × Non-white Teacher interaction. MEANTHETA, an algebra test score z-scored within the whole sample, may be related to 9th-grade teacher's input, as the baseline survey was conducted in Fall 2009 when the students were already in 9th grade. If a student took the test early in Fall 2009, then the connection between Non-white student × Non-white Teacher would be very weak. Table 4 also shows that Non-white student × Non-white Teacher does not significantly impact unique teacher-specific MEANTHETA scores either. Columns 2 and 4 in Table 4 demonstrate that Non-white student × Non-white Teacher does not significantly affect 8th-grade math/science GPA of the participating students. An additional falsification test, based on the main model, Equation 2, is also conducted.

Column 2 and 4 in Table 4 show that Non-white student × Non-white Teacher does not have a significant impact on 8th grade math/science GPA of the participating students. I also do an additional falsification test that is based on the main model, Equation 2.

$$Y_{ij,t-1} = \alpha_{j,t} + \gamma_{i,t} + \mathbf{X}'_{ij,t}\beta + \mathbf{D}'_{ij,t}\Omega + \epsilon_{ij,t} \;\; \forall \; j \in \{S, M\} \tag{5}$$

The second falsification test would measure the effect of $D_{ij,t}$ on past achievement - $Y_{ij,t-1}$ - in the context of the current analysis. Since any teacher-survey information is not available for any period later than the Fall 2009, it is beyond the scope of this paper to estimate the effect of $D_{ij,t+1}$ on $Y_{ij,t}$[22]. Table A.8, shows that there is no significant impact of $D_{ij,t}$ on $Y_{ij,t-1}$. To ensure, that students were not matched with their current math and science teachers in the 8th grade, I only consider the samples of students who were attending schools in Fall 2009 that did not include 8th grade. None of the coefficient estimates of the demographic mismatch categories are statistically significant, which means it is not likely that the effect of demographic mismatch in Fall 2009 is spuriously connected to achievement through some unknown factor that also drives past achievement.

6.3 Selection Bias

The sorting tests have established that demographic match or mismatch in the analytical sample is not related to the average teacher-specific student achievement. In the survey sample, not all students take math and science in the 9th grade. If the selection into math/science courses is merit-based, then the impact of demographic mismatch may be biased downward. More talented students who are selected into STEM courses would find it easier to mitigate the negative impact of the mismatch. The panel structure eliminates unobserved and observed invariant factors that might have led to selection in STEM classes. Moreover, in the 9th grade, students take foundational or basic STEM classes, which may be necessary for high school completion. This setup would limit the possibility of self-selection into different classes.

[22]The effect of $D_{ij,t}$ on $Y_{ij,t+1}$ could be estimated to see if the relationship between demographic mismatch and achievement was spurious, but it is possible that demographic mismatch would also continue in the next grade. In that case, an additional measure to separate future demographic mismatch, $D_{ij,t+1}$, from the $D_{ij,t}$ would be necessary. However, HSLS:09 does not include a teacher survey after baseline wave.

I conduct an additional test to determine if selection into Fall 2009 math/science classes was merit-based.

The selection bias test utilizes the panel structure of the data and estimates a student fixed-effects model. The main independent variable is the standardized grade in the highest-level math/science course in the 8th grade, and the outcome is whether math was taken in Fall 2009. The results of this test are presented in Table 5. The coefficient estimate for ZG8 is not statistically significant, indicating that there is little evidence of merit-based selection into Fall 2009 math and science classes. This test uses all available observations from the data source. The sample used for this test is considerably larger since teacher and principal survey variables, which are major sources of missing values in HSLS:09, are not included here. It's important to note that not all students take both math and science courses; some students take math but not science, and some take science but not math. Therefore, *within* students, the course-selection indicator would vary. In the 9th grade, students mainly take courses that are required for graduation, such as algebra, integrated math, geometry, etc. As a result, achievement-based course selection was much less likely in the 9th grade.

6.4 Teachers' Race and Student Achievement

Before discussing the results from estimating equation 2, I discuss "pre-baseline" results from a pooled regression analysis that allows readers to understand how the effect of demographic matching changes depending on the model we fit over the sample. The main model of interest in this paper uses a panel data structure. Such a model controls for factors that are invariant to the panel variable. A "pre-baseline" model offers more flexibility to observe race-related patterns. In this paper, the primary outcome of interest is 9th-grade GPA, which varies between science and math. 9th-grade GPAs are z-scored at the school level. Table 6 provides results from a pooled regression. Results in each column in this table differ only in the race categories of the teachers. When the whole sample is considered, Black and Hispanic teachers have negative impacts, while White and Asian teachers have positive impacts on STEM achievement. These "raw" results from the pooled regression do not control for past achievement, the various observed and unobserved drivers of student achievement, the effect of the school, etc. Therefore, the race indicators are most likely picking up average school quality in addition to their own effects.

In Table 7, we see a different picture after splitting the student sample by race. In column 1, I include all teacher race indicators, keeping White teachers as the reference group. None of the race categories appear to generate any significant impact on 9th-grade GPA, as shown in the first column. In columns 2, 3, and 4, I fit the pooled model on the samples of Black students, Hispanic students, and Asian students, respectively. The results in Table 7 tell a different story than Table 6. The impact of Black students being taught by a Black teacher is positive and statistically significant. The same is true for the Hispanic student sample. In both Tables, 6 and 7, the pooled model only considers a few control variables. Family income and parents' educational achievement are not considered as controls. Table A.3 includes region and locale control variables besides family income and one parent's educational indicator. For all student samples, family income and parent 1's education (whether he/she has a college degree) produce positive impacts on 9th-grade standardized GPA. In column 2, Table A.4, the estimated effect of having a Black teacher on Black students is statistically significant. In Columns 3, 4, and 5, the effect of having the same-race teacher is not statistically significant. In Table A.4, the teachers' race indicators are formulated differently; three variables presented are - whether the student faces a teacher with a different race, whether she/he faces a teacher of the other sex or both. The whole sample, including the Black sample of students, experiences negative impacts from having teachers of a different racial identity.

6.5 Main Results

Estimates of Equation 2 are presented in Table 8. Having a different-sex teacher appears to have a statistically significant negative impact on Z-scored 9th-grade GPA in math/science courses (ZGPA9). Its effect is statistically indistinguishable from zero for the Hispanic and female samples. The Asian sample sees a statistically significant impact of all three demographic mismatch categories on ZGPA9. Further stratification shows that Black female students face the statistically significant negative impact of having an other-sex and both other-race and other-sex teacher (Table 9).

The within-student panel does not require the inclusion of variables that are invariant within students. The baseline model includes teacher and school-related control variables that vary between the science and math courses or science and math teachers. HSLS:09 provides a wide variety of teacher-survey instruments. I include a parsimonious selection of teacher-survey instruments as controls because teacher quality and school quality are not likely to vary widely even though at least two different teachers (math and science) are reporting them. Teacher instruments are *whether the highest degree major was in a STEM field, years of experience in teaching high school students, percentage of teachers from Spring 2009 returning to teach in Fall 2009, highest degree earned by the teacher, whether advanced math courses are assigned to all or most math teachers, whether students dropping out is a problem*. Student effort put into studying math and science might not be the same. There is no explicit measure of effort levels varying between the two courses. I include hours spent doing math/science homework per week as an additional control variable in the baseline equation.

The rest of this section is dedicated to discussing robustness checks of the baseline results in Tables 9 and 10, and investigating potential channels through which demographic mismatch between teachers and students impacts student achievement. The robustness checks include various measures of student achievement that could be affecting 9th-grade math/science GPA via demographic mismatch. I extend the baseline results by including past achievement as a control variable, the highest-level 8th-grade math, and science course indicators and 9th-grade course indicators in Tables 10, 12, and 13. These extensions also serve the purpose of sensitivity analyses on the main model. First, Table 10 shows that including past grade ZG8 as a control variable makes the coefficients in Table 10 not so different from those in Table 9. Second, in Table 13, the baseline regression has been extended by both ZG8 and the indicator of the highest STEM course of 8th grade.

I develop alternative regression specifications by adding different types of fixed effects and control variables to equation 2. I use the more stratified samples like in Table 9 whenever possible for the robustness checks. However, splitting the sample by both races leaves too few observations for some of the robustness checks. Further, when interaction terms are applied, some demographic categories - like those in Table 9 - are not identifiable due to a lack of variation in their values. In those cases, I use the same sample division like that in Table 10. In another alternative specification, I add the unique teacher fixed effects besides course fixed effects to the baseline model in Equation 2 and estimate the effect of demographic mismatch. The coefficient estimates in Column 6 in Table 12 for Black female students are close to the baseline in Table 9.

HSLS:09 respondent students mention factors such as parental encouragement, teachers' encouragement, personal enjoyment, career development, and love for the challenge as reasons for taking STEM courses. The statistical description of these factors is provided in Table A.1. In Table 14, the baseline model is extended with interaction terms between D_{ij} and teachers' encouragement. Teachers' encouragement - TEACHER in Table 14 - is coded 1 when students report teachers' encouragement as a reason for taking math in 9th grade. In the lower panel, marginal effects of a teacher at levels of D_{ij} are shown. In columns 1 and 5 of Table 14, for Hispanic and Asian students, teachers' encouragement generates positive impacts on achievement, neutralizing the negative impacts of demographic mismatch.

The student fixed effects in equation 2 are not only useful for controlling for student-specific observed and unobserved factors but also for the effect of the average quality of the teachers, their beliefs, and mindsets. HSLS:09 provides a list of science and math teachers' beliefs and attitudes. This list of variables allows us to control for attitudinal effects from teachers affecting achievement through demographic mismatch. To elaborate with an example, the statistical description in Tables 1 and 2 showed that Black students, on average, see lower levels of student achievement. If White teachers in Black-majority schools are of low quality where quality is heterogeneous across courses and schools, and an aspect of being low quality is being skeptical about student success, then demographic mismatch would be picking up the negative effect of teacher beliefs and attributes that are at odds with promoting student success. To check if that is the case, I include some teacher belief indicators that might have a negative impact on student outcomes in the baseline model (equation 2) and provide the estimated results in Table A.7. The teacher belief variables are described in Table A.2. Compared to the baseline results in Table 9, the coefficient estimates of demographic mismatch in Table A.7 are not different by a considerable margin.

6.6 Alternative Outcomes

In addition to 9th-grade STEM GPA, the main outcome variable of this paper, I examine the effect of demographic mismatch on a few other student achievement measures. Tables 15 and 16 provide the estimated effect of demographic mismatch on total math/science AP credits in high school (APC) and high-school math/science GPA, respectively (HGPA). High school GPA in math and science is calculated by collecting all math and science course grade points from the 9th grade. A statistically significant impact of demographic mismatch on AP credits and high school GPA would indicate that demographic mismatch not only negatively affects current course outcomes but can also worsen longer-term educational outcomes[23]. For estimating the results discussed in this section, I primarily use the same set of right-hand side variables as those used in Tables 9 and 10.

Table 15 shows that demographic mismatch lowers AP credits for Black males and Asian females. On the other hand, demographic mismatch in Table 16 negatively affects a wider range of samples, including White females, Hispanic females, Hispanic males, Black males, and Asian females. Compared to the baseline results in Tables 8 and 9, the results in Tables 15 and 16 demonstrate that demographic mismatch has a longer-term negative impact that lasts throughout the high school lives of some demographic groups. In comparison, the baseline results did not show any negative impact for Hispanic female students, Hispanic male students, and Black male students.

As HGPA and APC are later outcomes than 9th-grade GPA (ZGPA9), they may capture demographic mismatch exacerbated by mismatch in multiple grades

[23]HGPA is standardized at the school level, while APC contains only positive numbers and can be compared across schools, so it is not transformed or standardized.

or classes. On the other hand, estimates lacking statistical significance may be driven by the fact that demographic mismatch led to self-selection (or outcome-driven school-authorized) out of elective math and science courses, weakening the link between end-of-high-school outcomes such as HGPA and APC[24]. Further, this allows the possibility that students would have some opportunity to match with teachers they like, possibly deflating the effect of initial demographic mismatch in 9th grade. These findings about APC and HGPA mainly hint at the longevity of the negative effect of demographic mismatch, but they may also be biased. One cannot identify the proper channel through which the effect is conducted. A model that contains outcomes for every grade could be used to address the question of the longevity of demographic-mismatch-related loss for students.

In addition to these results, Table A.6 shows the impact of demographic mismatch on 9th-grade math/science outcomes[25]. Many authors examine self-efficacy in math, science, and other courses as important inputs to educational production (see Chen and Usher, 2013). As multiple student-specific opinions of their own competence are combined, the exact source of a student's efficacy connected to demographic mismatch cannot be definitively outlined. Moreover, self-efficacy is constructed using subjective inputs from students. The average minority student assigned to an "other-race-and-other-sex" teacher may start feeling less confident about the factors that make up self-efficacy. I present the impact of demographic mismatch on self-efficacy in Table A.6. The results show that the effect of demographic mismatch on self-efficacy is very strong for Black males and Asian males.

6.7 Demographic Mismatch Channels

In this section, I examine the potential of specific school and teacher variables as conduits for the negative impact of demographic mismatch on minority students' achievement. The High School Longitudinal Study of 2009 (HSLS:09) conducted

[24]One caveat is that most schools require a minimum number of math and science classes to graduate, so the scope for opting out is mostly at the three- or four-course margin.

[25]Self-efficacy is a standardized variable that presents the scale of the student's efficacy in math or science. This variable is provided in HSLS:09 and is created through principal components factor analysis. The inputs to this scale were variables that rated how prepared the student feels about the math/science tests, how well the student understands the math/science textbooks, how confident the student is about his/her skills in math/science, and how confident the student is that she/he would excel in the math/science course. The answers to these questions were recorded on a Likert scale.

interviews with school administrators, gathering data on a broad spectrum of school characteristics. These variables may contribute to the variation in the effect of demographic mismatch. I investigate four such variables: (1) the percentage of students repeating 9th grade in a school, (2) the percent capacity to which a school is filled, (3) the percentage of non-white students, and (4) math and science teachers' observations regarding whether student unpreparedness is a problem for the school. Variables 1, 2, and 3 are likely related to school-level factors with potential negative effects on students. For instance, overcrowding can occur when a school's enrollment exceeds or nears its capacity, which can have a negative impact on student outcomes (Ready et al., 2004). A higher proportion of students repeating the 9th grade generally signifies lower average student abilities and achievement (Iachini et al., 2016). Lastly, attending schools with less racial diversity can intensify the self-perception of being a minority student. Generally, minority students may seek peers from the same demographic backgrounds who share similar life experiences. In schools that are less racially diverse, a demographic match between a minority teacher and a minority student can meet this need, while demographic mismatch between them would not. Variables 1, 2, and 3 do not vary within students; thus, I use their medians to split the analytical sample into two parts. This allows the observation of whether the demographic mismatch effect varies between the two parts.

Table 17 shows that across the sample, demographic mismatch is concentrated in schools where 8% or more of students repeat 9th grade. The 75th percentile of the variable "percentage of students repeating 9th grade in a school" is 8%, which I use as the cutoff to split the sample[26]. The results show that in schools where the percentage of 9th-grade repeaters is over 8%, both the female sample and the Black sample experience a negative effect of being assigned to an "other-sex and other-race" teacher. The next school characteristic of interest is the percent capacity to which a school is filled. The median of this variable is around 91%. Table 18 shows that across the analytical sample, Black students in schools that

[26]The median value for this variable is 1, signifying that in most schools in the sample, 1% or fewer students repeat 9th grade. However, I consider the 75th percentile value of this variable, which is 8%, as a 1% repeat rate might not sufficiently indicate a concerningly low level of student abilities.

are running at 91% student enrollment capacity or above experience a negative impact of being assigned to a different-sex and different-race teacher. However, the same demographic mismatch coefficient estimate for Black students in schools running below 91% of student enrollment capacity is statistically indistinguishable from zero. Demographic mismatch, which in the ideal scenario should have a null effect on student achievement, may become active in overcrowded schools. In such schools, teachers may have to teach large classes with a limited scope of having a more personal connection with the students. Such a constraint could enhance the minority student's need for teacher expectation or the so-called Pygmalion effect, which in-class demographic mismatch may not provide.

Table 19 presents the significant effect of demographic mismatch in schools where the proportion of minority students is below the sample median of 22%. As discussed earlier, the literature on the role-model effect suggests that minority students may need support from teachers who share the same demographic background. The results in Table 19 could be interpreted as evidence of the detrimental impact of demographic mismatch for minority students in schools where non-White students are less represented. To illustrate, the results in Table 19 show that especially, Black and Hispanic students likely experience the demographic mismatch effect in less racially diverse schools. This channel may work to elevate the minority student's need for teachers of the same demographic background.

The final variable under consideration is a subjective measure of overall student preparedness from the science and math teachers' questionnaire. This variable varies between math and science courses. This variable is interacted with the demographic mismatch variables in Table 20. The results show that demographic mismatch interacting with the binary variable - whether the teacher considers student preparedness - can negatively impact student achievement. Column 3 in Table 20 shows that female students experience a negative effect of the interaction term between being assigned to a same-sex and different-race teacher and the teacher(s) considering student unpreparedness was a problem in the school. While student unpreparedness is generally expected to negatively impact achievement, the interaction term suggests that for female students, the demographic mismatch effect can increase with peer unpreparedness.

7 Conclusion

In this paper, I present a model that estimates the impact of demographic mismatch on 9th-grade math/science course achievements. The importance of studying the effect of demographic mismatch on math/science outcomes lies in the fact that high-school math and science courses are foundations of future tertiary STEM education and that demographic test score gaps can be transmitted to post-secondary levels. I also focus on how demographic mismatch affects minority students as a racial gap in STEM achievement exists in the U.S. today. I use unique nationally representative survey data of 9th-grade high school students in the U.S. that contain demographic and career information of math and science teachers. The data allows me to analyze within-student variations in achievement and employ student fixed-effects to identify the effect of demographic mismatch with their teachers. I do not find any evidence of differential sorting or merit-based math/science course selection. The baseline results show that Black female students experience a significant loss in achievement (approximately 0.3 standard deviations) due to being assigned to a different-sex and different-race teacher in the 9th grade. This effect appears to be robust in some extended regression specifications.

Overall, the results complement the findings in Gershenson et al. (2016), Fairlie et al. (2014), and Sansone (2017). The systemic negative effect of demographic mismatch deserves more research, especially regarding how demographic mismatch operates in the classroom. The channels through which demographic mismatch operates have been briefly explored in this paper. By analyzing 9th-grade students' self-reported motivations for choosing math and science courses—such as teacher encouragement—in situations where course options are limited, I demonstrate that teachers' encouragement can positively impact some subsets of minority students on average. However, this beneficial effect can be neutralized by a demographic mismatch.

The observed adverse impact of demographic mismatch can be linked to the Golem effect, which is grounded in the assumption that student-teacher assignments do not consider individual preferences, as validated by sorting tests. However, it is plausible that even when demographic mismatch occurs randomly, it may still be influenced by the unobservable factor of teacher quality, particularly among underperforming non-minority teachers. Furthermore, assessing the Golem effect is challenging, especially in cases where course outcomes like GPA or letter grades lack objective measures. Moreover, the demographic mismatch in the dataset I employ does not result from controlled randomized assignment. Therefore, the primary aim of this paper is to illustrate the negative association between demographic mismatch and math/science outcomes, which could, in part, be attributed to the Golem effect. I also investigate potential mechanisms through which demographic mismatch may operate, including the possibility of an increased need for minority students to have teachers of the same race and gender.

I explore several mechanisms linking demographic mismatches with student achievement. Ideally, a student's academic outcome should remain unaffected by demographic matches or mismatches between teachers and students. Yet, in certain instances, the race and gender of a teacher can significantly influence the role of demographic matching and mismatching in shaping student achievement. These factors include overcrowded schools, lower average student abilities (as indicated by a high percentage - 8% or above - of 9th-grade repeaters), and teachers' assessments that student unpreparedness poses a problem for the school.

A highly significant mechanism revealed in the analysis is the racial diversity within schools. Notably, Black students exhibited a marked decrease in academic outcomes when attending schools with low racial diversity (where non-White students comprised less than 22%). As discussed in the role-model effect literature, minority students may gravitate towards teachers from similar demographic backgrounds due to shared life experiences. A demographic mismatch, particularly for Black students in less racially diverse schools, could amplify their self-perception as minorities, thus heightening their desire for teachers from the same demographic background as role models.

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Tables

Table 1: Key Variables to Analyze Demographic Mismatch - Student Categories

Variable	(1) All	(2) White	(3) Non-White	(4) Black	(5) Male	(6) Female
Outcomes						
9th grade STEM GPA	2.66	2.76	2.51***	2.24***	2.54	2.77***
STEM AP Credits	0.24	0.22	0.27***	0.15***	0.23	0.24
High School STEM GPA	2.47	2.57	2.32***	2.10***	2.34	2.60***
Self-efficacy	0.07	0.05	0.09***	0.21***	0.18	-0.36***
Explanatory Vars.						
Different Sex Teacher	0.49	0.48	0.49	0.47	0.56	0.40***
Different Race Teacher	0.41	0.06	0.93***	0.90***	0.41	0.40
Teacher has STEM degree	0.41	0.27	0.29	0.28***	0.29	0.28
Teachers' Experience	10.5	11	10	10***	10.5	10.4***
Teacher has Master's	0.52	0.52	0.52	0.52	0.52	0.52
Teaching Advanced Courses	0.68	0.67	0.70***	0.71***	0.68	0.67
Number of Certified Teachers	9.01	8.33	10.05***	9.33***	9.12	8.90***
Disruption is a problem	0.42	0.40	0.46***	0.48***	0.43	0.41***
Dropout is a problem	0.43	0.41	0.48***	0.46***	0.44	0.43
Homework (hrs. per day)	1.55	1.53	1.59***	1.62***	1.51	1.61***
Homework (hrs. per day) squared	3.08	2.97	3.24***	3.34***	2.95	3.21***
N	16,730	10,080	6,650	1,360	8,300	8,430

The analytical sample has the structure of an unbalanced panel. Two observations for each course - math and science - are associated with 82% of the students. The sample Teacher's Experience = how many years the teacher taught math/science to 9th to 12th grade students. Teacher has Master's = 1 if the teacher has a Master's or a higher-level degree, 0 if the teacher has a Bachelor's or similar degree. Teaching Advanced Courses = 1 if the most advanced courses are allocated to mostly to the senior teachers. Dropout is a problem = Teacher thinks that students dropping out of class is a problem in this school. Disruption = Teacher thinks that student disruption is a problem in this school. Homework = self-reported hours per day student spends doing homework. Homework squared = previous variable squared.
***p<0.01, **p<0.05, and *p<0.1 in column 3, 4, 6 refer to mean-difference t tests between column 2 and 3, 2 and 4, and 5 and 6 respectively.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 2: Key Variables to Analyze Demographic Mismatch - Teacher Categories

Variable	(1) All	(2) White	(3) Non-White	(4) Black	(5) Male	(6) Female
Outcomes						
9th grade STEM GPA	2.66	2.68	2.50***	2.35***	2.65	2.67
STEM AP Credits	0.24	0.24	0.22**	0.19	0.22	0.25***
High School STEM GPA	2.47	2.49	2.37***	2.32***	2.45	2.49***
Self-efficacy	0.07	0.07	0.10	0.13	0.06	0.08
Explanatory Vars.						
Different Sex Student	0.49	0.48	0.46	0.43***	0.49	0.48**
Different Race Student	0.41	0.37	0.75***	0.74***	0.40	0.42
Teacher has STEM degree	0.28	0.28	0.31***	0.23***	0.30	0.27***
Teachers' Experience	10.5	10.68	8.88***	8.51***	11.2	9.99***
Teacher has Master's	0.52	0.52	0.55***	0.56***	0.52	0.52***
Teaching Advanced Courses	0.68	0.68	0.70***	0.62**	0.66	0.70
Number of Certified Teachers	9.01	8.87	10.25***	9.40***	8.72	9.22***
Disruption is a problem	0.42	0.42	0.49***	0.49***	0.49	0.40***
Dropout is a problem	0.43	0.43	0.51***	0.52***	0.41	0.46
Homework (hrs. per day)	1.55	1.62	1.53***	1.62***	1.60	1.51***
Homework (hrs. per day) squared	3.08	3.07	3.24***	2.80***	3.21	2.95***
N	16,730	15,060	1,670	520	6,970	9,770

There are two observations per student. Teacher's Experience = how many years the teacher taught math/science to 9th to 12th grade students. Teacher has Master's = 1 if the teacher has a Master's or a higher-level degree, 0 if the teacher has a Bachelor's or similar degree. Teaching Advanced Courses = 1 if the most advanced courses are allocated to mostly to the senior teachers. Dropout is a problem = Teacher thinks that students dropping out of class is a problem in this school. Disruption = Teacher thinks that student disruption is a problem in this school. Homework = self-reported hours per day student spends doing homework. Homework squared = previous variable squared.
***p<0.01, **p<0.05, and *p<0.1 in column 3, 4, 6 refer to mean-difference t tests between column 2 and 3, 2 and 4, and 5 and 6 respectively.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 3: Test for Race-based Endogenous Sorting

	(1) NWT	(2) NWT	(3) NWT	(4) NWT
(a) Student non-white	0.00358	0.00431	0.00336	0.00316
	(0.00463)	(0.00466)	(0.00464)	(0.00464)
(b) Teacher-specific MEANTHETA	0.00904	0.00602		
	(0.00541)	(0.00691)		
(c) Interaction between (a) and (b)		0.00517		
		(0.00567)		
(d) Teacher-specific Mean Past Grade (ZG8)			0.0142	0.00684
			(0.00847)	(0.0125)
(e) Interaction between (a) and (d)				0.0128
				(0.0118)
Constant	0.994***	0.993***	0.998***	0.997***
	(0.00363)	(0.00361)	(0.00255)	(0.00264)
N	16730	16730	16730	16730
adj. R^2	0.518	0.518	0.518	0.518

Standard errors in parentheses. Standard Errors are clustered at school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
School × Course fixed effects are included in estimating results in each column.
NWT = Non-white Teacher indicator. I find unique math and science teachers in every school using variables from teacher questionnaire. I create two mean scores specific to each unique teacher. The first mean score variable is Teacher-specific MEANTHETA. Theta Scores are standardized algebra test scores built in the survey. This score has not been seen by the teachers or the schools. I create unique teacher specific theta score. The second mean score variable comes from averaging the past z-scored grade of the highest math/science course the student took in 8th grade over students taught by a unique teacher.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 4: Test for Endogenous Race-based Sorting Affecting Average Teacher-specific Achievement

	(1) MEANTHETA	(2) ZG8	(3) MEANTHETA	(4) ZG8
Non-white Student	-0.00972	0.00655	0.119	-0.00649
	(0.0577)	(0.0371)	(0.0737)	(0.0310)
Non-white Teacher	0.0873	0.0585	0.189	0.00113
	(0.0748)	(0.0495)	(0.6031)	(0.0246)
Non-white Student×Non-white Teacher	0.0637	0.0439	-0.0948	0.0417
	(0.0590)	(0.0386)	(0.0760)	(0.0326)
Constant	0.304***	-0.0757	-0.371***	0.00271
	(0.0750)	(0.0491)	(0.0615)	(0.0220)
N	16730	16730	16730	16730
adj. R^2	0.392	0.008	0.003	0.001

Standard errors in parentheses. Standard Errors are clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

- School × Course fixed effects are included in estimating results in column 1 and 2. Course fixed effects are included in estimating results in column 3 and 4.
- The two dependent variables MEANTHETA and ZG8 are mean scores specific to each unique teacher. The first mean score variable (MEANTHETA) comes from the theta scores presented in the survey. Theta Scores are standardized algebra test scores built in the survey. This score has not been seen by the teachers or the schools. The second mean score variable (ZG8) comes from averaging the past z-scored grade of the highest math/science course the student took in 8th grade over students taught by a unique teacher.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 5: Test for Selection Bias in *within*-student Panel Model

	(1) F09	(2) F09	(3) F09	(4) F09	(5) F09	(6) F09	(7) F09	(8) F09
ZG8	0.00134	0.00519	-0.00359	-0.0114	-0.00123	0.0174	0.00119	0.00151
	(0.00273)	(0.00406)	(0.00441)	(0.00935)	(0.00707)	(0.0124)	(0.00400)	(0.00398)
Science FE	-0.0372***	-0.0357***	-0.0398***	-0.0500***	-0.0438***	-0.0103	-0.0435***	-0.0310***
	(0.00485)	(0.00554)	(0.00606)	(0.0131)	(0.00846)	(0.0101)	(0.00583)	(0.00560)
Constant	0.924***	0.936***	0.906***	0.894***	0.893***	0.918***	0.921***	0.926***
	(0.00231)	(0.00263)	(0.00284)	(0.00606)	(0.00401)	(0.00571)	(0.00279)	(0.00265)
Sample	All	White	Non-white	Black	Hispanic	Asian	Male	Female
N	27570	15900	11670	2540	3960	2150	13830	13740
adj. R^2	0.015	0.014	0.016	0.020	0.020	0.003	0.019	0.011

Standard errors in parentheses. Standard Errors are clustered at school level. ZG8 = Grade received in the highest math/science course taken in 8th grade. F09 = Binary variable, 1 if student has taken math and science in 9th grade.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), “Base-year Survey, 2009.”

Table 6: Pooled OLS Regression Results - Teachers' Race

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9
Black Teacher	-0.333***			
	(0.0322)			
White Teacher		0.121***		
		(0.0181)		
Hispanic Teacher			-0.221***	
			(0.0260)	
Asian Teacher				0.421***
				(0.0302)
Male Teacher	-0.209***	-0.211***	-0.214***	-0.213***
	(0.0181)	(0.0181)	(0.0181)	(0.0180)
T has a STEM Degree	0.0472***	0.0500***	0.0492***	0.0409**
	(0.0182)	(0.0182)	(0.0180)	(0.0180)
T's Experience of teaching 9-12 grade yrs.	0.00331***	0.00326***	0.00324***	0.00324***
	(0.00101)	(0.00102)	(0.00102)	(0.00102)
T has Master's or higher degree	0.0310**	0.0295*	0.0247	0.0240
	(0.0155)	(0.0157)	(0.0157)	(0.0155)
Science FE	0.0419***	0.0448***	0.0443***	0.0427***
	(0.0107)	(0.0108)	(0.0107)	(0.0105)
Number of Certified Full-time Ts	0.00203**	0.00320***	0.00266**	-0.000769
	(0.00102)	(0.00104)	(0.00104)	(0.00107)
Senior T teaches Advanced Courses	-0.0251	-0.0277*	-0.0254	-0.0174
	(0.0156)	(0.0158)	(0.0158)	(0.0156)
Disruption is a Problem	-0.0541***	-0.0555***	-0.0554***	-0.0552***
	(0.0170)	(0.0171)	(0.0170)	(0.0170)
Dropout is a Problem	-0.0624***	-0.0672***	-0.0687***	-0.0707***
	(0.0167)	(0.0168)	(0.0167)	(0.0165)
Homework hrs. daily	0.0333	0.0337	0.0260	0.00937
	(0.0310)	(0.0309)	(0.0308)	(0.0314)
Homework^2 hrs. daily	-0.00350	-0.00355	-0.00269	-0.000751
	(0.00612)	(0.00609)	(0.00605)	(0.00622)
Constant	0.0708*	-0.0398	0.0790*	0.0646
	(0.0405)	(0.0429)	(0.0408)	(0.0412)
N	16730	16730	16730	16730
adj. R^2	0.025	0.019	0.022	0.029

Standard errors in parentheses.
Standard Errors are clustered at the level of school.
T= Teacher

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 7: Pooled OLS Regression Results - Differences in 9th Grade GPA in Demographic Samples

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9
Asian Teacher	0.0876				0.0934
	(0.0571)				(0.136)
Black Teacher	0.00986	0.202**			
	(0.0473)	(0.0858)			
Hispanic Teacher	0.00780			0.107*	
	(0.0335)			(0.0618)	
White Teacher	-		-0.00383		
	-		(0.0428)		
Male Teacher	-0.0405***	0.000284	-0.0370*	-0.0239	0.0292
	(0.0155)	(0.0511)	(0.0196)	(0.0413)	(0.0511)
T has STEM Degree	0.0439**	0.112*	0.0333	0.0752	0.0254
	(0.0179)	(0.0662)	(0.0228)	(0.0475)	(0.0542)
T's Experience of teaching 9-12 grade yrs.	0.00359***	0.00153	0.00236*	0.00278	0.000461
	(0.00101)	(0.00349)	(0.00127)	(0.00276)	(0.00317)
T has Master's or higher degree	0.0272*	0.00508	0.0251	0.00301	0.110**
	(0.0156)	(0.0566)	(0.0192)	(0.0466)	(0.0541)
Science FE	0.0464***	0.0137	0.0580***	0.0122	0.0549
	(0.0108)	(0.0495)	(0.0146)	(0.0379)	(0.0476)
Number of Certified Full-time Ts	0.00145	0.00768	0.000476	-0.00282	0.00203
	(0.000960)	(0.00551)	(0.00192)	(0.00342)	(0.00384)
Senior T teaches Advanced Courses	-0.0298*	-0.0510	-0.0152	-0.00268	-0.0757
	(0.0158)	(0.0671)	(0.0201)	(0.0441)	(0.0549)
Disruption is a Problem	-0.0640***	-0.0637	-0.0463**	-0.117***	-0.0247
	(0.0169)	(0.0593)	(0.0212)	(0.0446)	(0.0539)
Dropout is a Problem	-0.0634***	0.0984	-0.0827***	0.0586	0.105*
	(0.0164)	(0.0658)	(0.0216)	(0.0497)	(0.0579)
Homework hrs. daily	0.0536*	0.0721	0.0227	0.158*	0.0283
	(0.0310)	(0.100)	(0.0379)	(0.0856)	(0.103)
Homework^2 hrs. daily	-0.00699	-0.00449	0.000981	-0.0395**	-0.0111
	(0.00611)	(0.0186)	(0.00732)	(0.0160)	(0.0208)
Constant	-0.0554	-0.470***	0.0142	-0.240**	0.332**
	(0.0397)	(0.153)	(0.0641)	(0.114)	(0.153)
Sample	All	Black	White	Hispanic	Asian
N	16730	1360	10080	2210	1290
adj. R^2	0.047	0.012	0.002	0.011	0.015

Standard errors in parentheses.
Standard Errors are clustered at the level of school.
In Column 1, "White" is the reference race category. T = Teacher

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 8: Baseline Panel Results of Demographic Mismatch

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9	(6) ZGPA9	(7) ZGPA9	(8) ZGPA9
Other Sex & same Race	-0.0375**	-0.0325*	-0.178*	-0.0203	-0.0503*	-0.0570	-0.399**	-0.699*
	(0.0184)	(0.0186)	(0.102)	(0.0262)	(0.0282)	(0.179)	(0.179)	(0.387)
Same Sex & other race	0.0326	0.0258	-0.0451	0.0194	0.0477	0.0672	-0.163	-0.474*
	(0.0378)	(0.0590)	(0.0704)	(0.0479)	(0.0576)	(0.103)	(0.154)	(0.249)
Other race & Other sex	0.0270	0.0571	-0.0520	0.0172	0.0405	0.0820	-0.263	-0.449*
	(0.0386)	(0.0560)	(0.0711)	(0.0529)	(0.0531)	(0.0987)	(0.163)	(0.254)
Sample	All	White	Non-white	Female	Male	Hispanic	Black	Asian
N	16730	10080	6650	8430	8300	2210	1360	1290
adj. R^2	0.016	0.011	0.016	0.018	0.015	0.016	0.015	0.040

Standard errors in parentheses. Standard Errors are clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Student ID is the panel variable. Course fixed effects are included in estimating results in all columns. The control variables used in deriving results in each column are 1. whether teacher has STEM degree (binary), 2. Years of experience the teacher has teaching 9-12 grades, 2. Number of S/M full-time teachers in school, 3. Senior teachers teach all advanced S/M courses (binary), 4. S/M teacher thinks disruption in classroom is a problem for the school (binary), 5. S/M teacher thinks tudents dropping out is a problem for the school (binary), 6. S/M homework hours per week squared. 7. S/M homework hours per week squared. S/M means science or math, it signifies variables varying between 9th grade science and math courses.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 9: Baseline Panel Results of Demographic Mismatch - Demographic Stratification

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9	(6) ZGPA9	(7) ZGPA9	(8) ZGPA9	(9) ZGPA9
Other Sex & Same Race	-0.0375**	-0.0134	-0.0525*	-0.218	0.181	-0.609***	0.127	-0.675	-0.831
	(0.0184)	(0.0262)	(0.0284)	(0.192)	(0.359)	(0.215)	(0.303)	(0.508)	(0.511)
Same Sex & Other Race	0.0326	-0.0113	0.0622	0.109	-0.0493	-0.293	0.235	-0.629	-0.290
	(0.0378)	(0.0659)	(0.110)	(0.139)	(0.164)	(0.197)	(0.206)	(0.477)	(0.260)
Other Sex & Other Race	0.0270	0.0613	0.0629	0.157	-0.0391	-0.379*	0.144	-0.548	-0.329
	(0.0386)	(0.0981)	(0.0648)	(0.144)	(0.156)	(0.206)	(0.233)	(0.481)	(0.268)
Sample	All	White Female	White Male	Hispanic Female	Hispanic Male	Black Female	Black Male	Asian Female	Asian Male
N	16730	5100	4980	1150	1050	650	700	650	650
adj. R^2	0.016	0.017	0.018	0.029	0.015	0.036	0.032	0.094	0.037

Standard errors in parentheses. Standard Errors are clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Student ID is the panel variable. Course fixed effects are included in estimating results in all columns. The control variables used in deriving results in each column are 1. whether teacher has STEM degree (binary), 2. Years of experience the teacher has teaching 9-12 grades, 2. Number of S/M full-time teachers in school, 3. Senior teachers teach all advanced S/M courses (binary), 4. S/M teacher thinks disruption in classroom is a problem for the school (binary), 5. S/M teacher thinks tudents dropping out is a problem for the school (binary), 6. S/M homework hours per week squared. 7. S/M homework hours per week squared. S/M means science or math, it signifies variables varying between 9th grade science and math courses.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 10: Baseline Specification Extended by Including Past Achievement

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9	(6) ZGPA9	(7) ZGPA9	(8) ZGPA9	(9) ZGPA9
Other Sex & Same Race	-0.0365**	-0.0117	-0.0540*	-0.195	0.195	-0.634***	0.189	-0.736	-0.876
	(0.0185)	(0.0261)	(0.0284)	(0.188)	(0.350)	(0.215)	(0.307)	(0.469)	(0.544)
Same Sex & Other Race	0.0319	-0.00215	0.0583	0.124	-0.0401	-0.299	0.260	-0.664	-0.246
	(0.0366)	(0.0638)	(0.108)	(0.137)	(0.159)	(0.191)	(0.206)	(0.443)	(0.232)
Other Sex & Other Race	0.0292	0.0838	0.0687	0.170	-0.0333	-0.394*	0.175	-0.565	-0.271
	(0.0375)	(0.0968)	(0.0634)	(0.143)	(0.152)	(0.205)	(0.234)	(0.447)	(0.240)
ZG8	0.113***	0.145***	0.0879***	0.0966**	0.0799	0.104	0.0671	0.290***	0.207**
	(0.0133)	(0.0254)	(0.0233)	(0.0468)	(0.0500)	(0.0785)	(0.0425)	(0.0536)	(0.102)
Sample	All	White Female	White Male	Hispanic Female	Hispanic Male	Black Female	Black Male	Asian Female	Asian Male
N	16730	5100	4980	1150	1050	650	700	650	650
adj. R^2	0.026	0.046	0.020	0.044	0.014	0.052	0.040	0.202	0.076

Standard errors in parentheses. Standard Errors are clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The control variables used in deriving results in each column are 1. whether teacher has STEM degree (binary), 2. Years of experience the teacher has teaching 9-12 grades, 2. Number of S/M full-time teachers in school, 3. Senior teachers teach all advanced S/M courses (binary), 4. S/M teacher thinks disruption in classroom is a problem for the school (binary), 5. S/M teacher thinks tudents dropping out is a problem for the school (binary), 6. S/M homework hours per week squared. 7. S/M homework hours per week squared. S/M means science or math, it signifies variables varying between 9th grade science and math courses. Additional right-hand-side variable: ZG8 = Grade the student earned in the highest math or science class in 8th grade; normalized at school level.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), “Base-year Survey, 2009.”

Table 11: Baseline Specification Extended by Including Past Achievement & 8th Grade Course indicators

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9	(6) ZGPA9	(7) ZGPA9	(8) ZGPA9	(9) ZGPA9
Other Sex & Same Race	-0.0282	-0.0169	-0.0397	-0.150	0.228	-0.362	0.0612	-0.881*	-0.952*
	(0.0180)	(0.0263)	(0.0273)	(0.227)	(0.348)	(0.295)	(0.230)	(0.457)	(0.542)
Same Sex & Other Race	0.0362	-0.0453	0.104	0.180	0.00269	-0.214	0.232	-0.660	-0.330
	(0.0368)	(0.0648)	(0.116)	(0.160)	(0.160)	(0.155)	(0.162)	(0.419)	(0.239)
Other Sex & Other Race	0.0342	0.103	0.0561	0.225	0.0506	-0.306*	0.151	-0.610	-0.354
	(0.0374)	(0.0895)	(0.0693)	(0.163)	(0.153)	(0.172)	(0.178)	(0.426)	(0.249)
ZG8	0.113***	0.145***	0.0879***	0.0966**	0.0799	0.104	0.0671	0.290***	0.207**
	(0.0133)	(0.0254)	(0.0233)	(0.0468)	(0.0500)	(0.0785)	(0.0425)	(0.0536)	(0.102)
Sample	All	White Female	White Male	Hispanic Female	Hispanic Male	Black Female	Black Male	Asian Female	Asian Male
N	16730	5100	4980	1150	1050	650	700	650	650
adj. R^2	0.029	0.053	0.021	0.085	0.077	0.113	0.053	0.323	0.150

Standard errors in parentheses. Standard Errors are clustered at school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
These results are estimated with the same set of control variables in the regression equation as those in Tables 8 and A.7. **Additional controls:** (1) ZG8 = Grade the student earned in the highest math or science class in 8th grade; normalized at school level and (2) dummy indicators of highest course in math/science in 8th grade, and (3) interaction terms (1)×(2)

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 12: Baseline Specification Extended by Including Unique Teacher Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9
Other Sex & Same Race	-0.0375**	-0.0134	-0.0525*	-0.218	0.181	-0.609***	0.127	-0.675	-0.831
	(0.0184)	(0.0262)	(0.0284)	(0.192)	(0.359)	(0.215)	(0.303)	(0.508)	(0.511)
Same Sex & Other Race	0.0326	-0.0113	0.0622	0.109	-0.0493	-0.293	0.235	-0.629	-0.290
	(0.0378)	(0.0659)	(0.110)	(0.139)	(0.164)	(0.197)	(0.206)	(0.477)	(0.260)
Other Sex & Other Race	0.0270	0.0613	0.0629	0.157	-0.0391	-0.379*	0.144	-0.548	-0.329
	(0.0386)	(0.0981)	(0.0648)	(0.144)	(0.156)	(0.206)	(0.233)	(0.481)	(0.268)
Sample	All	White Female	White Male	Hispanic Female	Hispanic Male	Black Female	Black Male	Asian Female	Asian Male
N	16730	5100	4980	1150	1050	650	700	650	650
adj. R^2	0.016	0.017	0.018	0.029	0.015	0.036	0.032	0.094	0.037

Standard errors in parentheses. Standard Errors are clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10. In addition to the baseline controls, the results in all the above columns are estimated after adding dummy indicators per unique teacher in each school. 67% of the observations correspond with 4 unique teachers in a single school. But the number of unique teachers are up to 19.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), “Base-year Survey, 2009.”

Table 13: Baseline Specification Extended by Including Past Achievement & 8th Grade Course indicators

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9	(6) ZGPA9	(7) ZGPA9	(8) ZGPA9	(9) ZGPA9
Other Sex & Same Race	-0.0282	-0.0169	-0.0397	-0.150	0.228	-0.362	0.0612	-0.881*	-0.952*
	(0.0180)	(0.0263)	(0.0273)	(0.227)	(0.348)	(0.295)	(0.230)	(0.457)	(0.542)
Same Sex & Other Race	0.0362	-0.0453	0.104	0.180	0.00269	-0.214	0.232	-0.660	-0.330
	(0.0368)	(0.0648)	(0.116)	(0.160)	(0.160)	(0.155)	(0.162)	(0.419)	(0.239)
Other Sex & Other Race	0.0342	0.103	0.0561	0.225	0.0506	-0.306*	0.151	-0.610	-0.354
	(0.0374)	(0.0895)	(0.0693)	(0.163)	(0.153)	(0.172)	(0.178)	(0.426)	(0.249)
ZG8	0.113***	0.145***	0.0879***	0.0966**	0.0799	0.104	0.0671	0.290***	0.207**
	(0.0133)	(0.0254)	(0.0233)	(0.0468)	(0.0500)	(0.0785)	(0.0425)	(0.0536)	(0.102)
Sample	All	White Female	White Male	Hispanic Female	Hispanic Male	Black Female	Black Male	Asian Female	Asian Male
N	16730	5100	4980	1150	1050	650	700	650	650
adj. R^2	0.029	0.053	0.021	0.085	0.077	0.113	0.053	0.323	0.150

Standard errors in parentheses. Standard Errors are clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10. Additional controls: (1) ZG8 = Grade the student earned in the highest math or science class in 8th grade; normalized at school level and (2) dummy indicators of highest course in math/science in 8th grade, and (3) interaction terms (1)×(2)

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 14: Teachers' Encouragement and Demographic Mismatch

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9	(6) ZGPA9	(7) ZGPA9	(8) ZGPA9
(a) Other Sex & same Race	-0.0296	-0.0249	-0.168*	-0.0105	-0.0446	-0.0786	-0.338*	-0.968**
	(0.0196)	(0.0198)	(0.0997)	(0.0281)	(0.0292)	(0.174)	(0.172)	(0.385)
(b) Same Sex & other race	0.0262	0.00859	-0.0234	0.0118	0.0468	0.0635	-0.135	-0.488*
	(0.0387)	(0.0654)	(0.0701)	(0.0498)	(0.0584)	(0.109)	(0.142)	(0.259)
(c) Other race & Other sex	0.0287	0.0476	-0.0234	0.0146	0.0472	0.0660	-0.216	-0.467*
	(0.0394)	(0.0615)	(0.0714)	(0.0551)	(0.0540)	(0.107)	(0.153)	(0.267)
(d) TEACHER	-0.0544	-0.0463	0.360*	-0.0171	-0.114	0.361*	0.637**	-0.116
	(0.0452)	(0.0475)	(0.188)	(0.0560)	(0.0704)	(0.212)	(0.306)	(0.520)
Interaction (a)×(d)	-0.0238	-0.0223	-0.0464	-0.0245	-0.0159	0.0813	-0.890**	0.815
	(0.0580)	(0.0581)	(0.268)	(0.0726)	(0.0909)	(0.352)	(0.367)	(0.575)
Interaction (b)×(d)	0.100	0.156	-0.332*	0.0828	0.129	-0.373*	-0.459	0.0475
	(0.0677)	(0.163)	(0.189)	(0.0854)	(0.109)	(0.225)	(0.318)	(0.522)
Interaction (c)×(d)	0.0673	0.153	-0.384**	0.0602	0.0834	-0.126	-0.748**	0.0891
	(0.0732)	(0.116)	(0.195)	(0.100)	(0.0969)	(0.237)	(0.352)	(0.533)
Sample	All	White	Non-white	Female	Male	Hispanic	Black	Asian
N	16730	10080	6650	8430	8300	2210	1360	1290
adj. R^2	0.019	0.025	0.023	0.022	0.017	0.026	0.055	0.068

Standard errors in parentheses. Standard Errors are clustered at school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10. Additional controls: TEACHER = 1 means that the student reported that he/she took 9th grade math or science because a teacher encouraged it.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 15: Demographic Mismatch and AP Credits

	(1) APC	(2) APC	(3) APC	(4) APC	(5) APC	(6) APC	(7) APC	(8) APC	(9) APC
Other Sex & Same Race	-0.00363	-0.00592	0.00237	0.0428	0.161	0.0454	-0.127	-2.050***	0.774
	(0.0151)	(0.0268)	(0.0228)	(0.162)	(0.128)	(0.0657)	(0.141)	(0.266)	(1.102)
Same Sex & Other Race	0.0206	-0.0849	0.0413	0.0804	0.178	-0.0257	-0.210*	-0.404*	0.375
	(0.0371)	(0.0842)	(0.0701)	(0.138)	(0.142)	(0.0389)	(0.117)	(0.235)	(0.375)
Other Sex & Other Race	0.0337	0.0112	0.133	0.120	0.217	-0.0344	-0.233*	-0.528**	0.404
	(0.0346)	(0.0654)	(0.0876)	(0.148)	(0.150)	(0.0559)	(0.133)	(0.256)	(0.384)
Sample	All	White Female	White Male	Hispanic Female	Hispanic Male	Black Female	Black Male	Asian Female	Asian Male
N	16730	5100	4980	1150	1050	650	700	650	650
adj. R^2	0.010	0.019	0.011	0.026	0.031	0.080	0.045	0.171	0.044

Standard errors in parentheses. Standard Errors are clustered at school level. APC = Math and Science AP credits. APC varies between math and science for each student because of the panel data structure.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Course fixed effects are included in estimating results in all columns. These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 16: Demographic Mismatch and High School Math and Science GPA

	(1) HGPA	(2) HGPA	(3) HGPA	(4) HGPA	(5) HGPA	(6) HGPA	(7) HGPA	(8) HGPA	(9) HGPA
Other Sex & Same Race	-0.0253	-0.0560*	0.0212	-0.685***	-0.403*	-0.159	-0.282	-1.288**	0.0243
	(0.0219)	(0.0320)	(0.0297)	(0.241)	(0.223)	(0.236)	(0.232)	(0.558)	(0.425)
Same Sex & Other Race	-0.0429	-0.0532	-0.130	-0.412**	-0.0433	-0.167	-0.263*	-0.806	-0.0791
	(0.0442)	(0.0748)	(0.123)	(0.173)	(0.127)	(0.174)	(0.138)	(0.529)	(0.274)
Other Sex & Other Race	-0.0358	0.0763	-0.00417	-0.377**	-0.0470	-0.140	-0.246	-0.987*	-0.00898
	(0.0451)	(0.120)	(0.0929)	(0.159)	(0.128)	(0.180)	(0.160)	(0.535)	(0.273)
Sample	All	White Female	White Male	Hispanic Female	Hispanic Male	Black Female	Black Male	Asian Female	Asian Male
N	16730	5100	4980	1150	1050	650	7000	650	650
adj. R^2	0.001	0.008	0.003	0.027	0.010	0.031	0.053	0.115	0.038

Standard errors in parentheses. Standard Errors are clustered at school level. HGPA = High School GPA. HGPA varies between math and science for each student because of the panel data structure.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Course fixed effects are included in estimating results in all columns. These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 17: Demographic Mismatch: Percentage of students that repeat 9th grade

8% or higher	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9	(6) ZGPA9	(7) ZGPA9
Other Sex & Same Race	-0.0974**	-0.0970**	-0.181*	-0.161**	-0.0116	-0.0681	-0.202
	(0.0398)	(0.0418)	(0.103)	(0.0633)	(0.0633)	(0.144)	(0.149)
Same Sex & Other Race	-0.104	-0.201*	-0.105	-0.133*	-0.0663	0.0747	-0.323**
	(0.0683)	(0.104)	(0.0959)	(0.0734)	(0.105)	(0.144)	(0.150)
Other Sex & Other Race	-0.0979	-0.0286	-0.121	-0.189**	0.00774	0.110	-0.295*
	(0.0716)	(0.138)	(0.100)	(0.0918)	(0.105)	(0.145)	(0.171)
N	4270	2160	2110	2130	2140	720	510
adj. R^2	0.018	0.017	0.019	0.017	0.010	0.017	0.058
Less than 8%	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9
Other Sex & Same Race	-0.0191	-0.0212	-0.0309	-0.0101	-0.0305	0.139	-0.344
	(0.0273)	(0.0193)	(0.124)	(0.0277)	(0.0291)	(0.204)	(0.224)
Same Sex & Other Race	0.0861	0.0905	0.0882	0.0680	0.102	0.107	-0.0356
	(0.0538)	(0.0738)	(0.0814)	(0.0552)	(0.0720)	(0.120)	(0.171)
Other Sex & Other Race	0.0902	0.0743	0.0911	0.0714	0.0967	0.148	-0.172
	(0.0571)	(0.0609)	(0.0819)	(0.0595)	(0.0660)	(0.118)	(0.182)
N	7650	8930	5420	7180	7180	1770	1060
adj. R^2	0.018	0.012	0.016	0.011	0.015	0.011	0.015
Sample	All	White	Non-White	Female	Male	Hispanic	Black

Standard errors in parentheses. Standard Errors are clustered at school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 18: Demographic Mismatch: Percent capacity to which school is filled

Below 91%	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9
Other Sex & Same Race	-0.0314	-0.0234	-0.264**	-0.0169	-0.0377	-0.115	-0.441
	(0.0259)	(0.0265)	(0.119)	(0.0385)	(0.0415)	(0.190)	(0.274)
Same Sex & Other Race	0.0260	0.00807	-0.0585	0.0340	0.0308	-0.0453	0.0248
	(0.0527)	(0.0846)	(0.0831)	(0.0613)	(0.0803)	(0.103)	(0.224)
Other Sex & Other Race	0.0171	0.0370	-0.0685	0.0457	0.00767	0.0186	-0.128
	(0.0531)	(0.0664)	(0.0903)	(0.0686)	(0.0715)	(0.106)	(0.233)
N	8350	4840	3500	4130	4210	1140	690
adj. R^2	0.016	0.013	0.014	0.019	0.014	0.010	0.027
91% or above	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9
Other Sex & Same Race	-0.0420*	-0.0422*	-0.0214	-0.0528	-0.0192	0.104	-0.188
	(0.0229)	(0.0231)	(0.119)	(0.0345)	(0.0334)	(0.200)	(0.125)
Same Sex & Other Race	0.0524	0.0500	0.0422	0.0149	0.0973	0.140	-0.180
	(0.0573)	(0.0958)	(0.0922)	(0.0698)	(0.0923)	(0.142)	(0.130)
Other Sex & Other Race	0.0634	0.0916	0.0496	-0.0160	0.146	0.161	-0.237*
	(0.0574)	(0.0950)	(0.0890)	(0.0769)	(0.0891)	(0.138)	(0.140)
N	6440	7520	4560	6040	6070	1490	890
adj. R^2	0.018	0.012	0.016	0.011	0.015	0.011	0.015
Sample	All	White	Non-White	Female	Male	Hispanic	Black

Standard errors in parentheses. Standard Errors are clustered at school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 19: Demographic Mismatch: Percentage of Non-White Students

22% or above	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9	(6) ZGPA9
Other Sex & Same Race	-0.0719**	-0.0811	-0.0697	-0.0617	0.0515	-0.210
	(0.0309)	(0.0919)	(0.0451)	(0.0495)	(0.156)	(0.144)
Same Sex & Other Race	-0.0150	0.0260	-0.0264	-0.00254	0.115	-0.0729
	(0.0455)	(0.0669)	(0.0580)	(0.0665)	(0.101)	(0.118)
Other Sex & Other Race	0.0179	0.0393	-0.000671	0.0418	0.185	-0.0964
	(0.0474)	(0.0705)	(0.0659)	(0.0616)	(0.401)	(0.136)
N	7560	4150	3820	3830	1470	960
adj. R^2	0.017	0.017	0.011	0.009	0.024	0.018
Below 22%	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9	ZGPA9
Other Sex & Same Race	-0.0151	-0.203	-0.0204	-0.00786	-1.148***	-0.00133
	(0.0232)	(0.201)	(0.0345)	(0.0335)	(0.285)	(0.264)
Same Sex & Other Race	0.0924	-0.102	0.0634	0.115	-0.969***	-0.827***
	(0.0829)	(0.163)	(0.100)	(0.124)	(0.247)	(0.199)
Other Sex & Other Race	0.0494	-0.123	0.0166	0.0795	-1.055***	-1.006***
	(0.0809)	(0.162)	(0.100)	(0.115)	(0.224)	(0.204)
N	7390	2100	3940	3990	580	340
adj. R^2	0.019	0.019	0.010	0.017	0.044	0.139
Sample	White	Non-White	Female	Male	Hispanic	Black

Standard errors in parentheses. Standard Errors are clustered at school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table 20: Demographic Mismatch × Students coming to class unprepared is a problem

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9	(6) ZGPA9
(1) Other Sex & Same Race	-0.00674	-0.224	0.0413	-0.0558	-0.116	-0.448**
	(0.0253)	(0.136)	(0.0382)	(0.0384)	(0.353)	(0.185)
(2) Same Sex & Other Race	0.0610	-0.00521	0.0765	0.0350	0.130	-0.130
	(0.0473)	(0.0922)	(0.0559)	(0.0703)	(0.176)	(0.146)
(3) Other Sex & Other Race	0.0306	-0.0361	0.00790	0.0344	0.0813	-0.309**
	(0.0466)	(0.0913)	(0.0645)	(0.0626)	(0.164)	(0.153)
(4) Unpreparedness a problem (=1)	0.00567	-0.0158	0.0617	-0.0670*	-0.0493	-0.103
	(0.0269)	(0.118)	(0.0386)	(0.0395)	(0.224)	(0.150)
(1)×(4)	-0.0549	0.159	-0.151***	0.0432	0.212	0.298
	(0.0342)	(0.190)	(0.0513)	(0.0496)	(0.446)	(0.215)
(2)×(4)	-0.0474	0.00119	-0.116*	0.0396	-0.0693	0.0523
	(0.0445)	(0.121)	(0.0610)	(0.0613)	(0.232)	(0.165)
(3)×(4)	0.0103	0.0576	-0.00529	0.0559	0.0848	0.220
	(0.0439)	(0.120)	(0.0693)	(0.0569)	(0.221)	(0.174)
sample	All	Non-White	Female	Male	Hispanic	Black
N	15750	6330	7830	7810	2080	1320
adj. R^2	0.017	0.014	0.013	0.015	0.017	0.014

Standard errors in parentheses. Standard Errors are clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Course fixed effects are included in estimating results in all columns. These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

A: Supplementary Tables

Table A.1: Additional Variable Means - Past Achievement, Reason for Taking Math/Science, and School Characteristics

Variable	(1) All	(2) White	(3) Non-White	(4) Black	(5) Male	(6) Female
ZGPA8	0.04	0.086	-0.014	-0.015	-0.043	0.011
θ	0.17	0.22	0.10	-0.20	0.168	0.141
	Reason for taking math/science in 9th grade					
Teacher's encouragement	0.11	0.12	0.11	0.079	0.10	0.13
Challenge	0.16	0.16	0.17	0.14	0.16	0.16
Parent's encouragement	0.14	0.15	0.13	0.09	0.13	0.15
Career	0.16	0.15	0.17	0.16	0.14	0.17
Enjoyment	0.16	0.15	0.17	0.16	0.14	0.17
	School characteristics - principal questionnaire					
9th grade repeat	3.92	3.45	4.63	4.89	3.94	3.90
% capacity to which school is filled	87.10	87.08	87.12	85.65	87.33	87.87
% of student body is Black	11.88	9.37	15.68	26.24	11.74	12.02
% of students are enrolled in Free Lunch	30.22	27.79	33.91	33.98	30.13	30.32
Bullying is a problem in the school (=1)	0.49	0.51	0.47	0.45	0.49	0.49

ZGPA8 = Z-scored 8th grade highest course GPA, θ = Mathematical theta score.
Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table A.2: Additional Teacher Survey Means

Variable	(1) All	(2) White	(3) Non-White	(4) Black	(5) Male	(6) Female
TXFAMILY	0.26	0.26	0.27	0.27	0.27	0.26
TXDISCIPLINE	0.70	0.71	0.69	0.69	0.71	0.69
TXSTUACHIEVE	0.41	0.40	0.43	0.44	0.42	0.40
TXPARENT	0.66	0.66	0.67	0.65	0.66	0.67
TXHOMEFX	0.16	0.15	0.17	0.16	0.16	0.16
TXABLRANGE	0.48	0.48	0.50	0.52	0.49	0.48
TXSESRANGE	0.19	0.18	0.22	0.25	0.19	0.19
Family Income	84,779.16	91,534.52	74,305.67	69,452.69	85,330.63	82,660.69
Parent 1 has College Degree	0.386	0.408	0.355	0.39	0.386	0.386

TXFAMILY = 1 if teacher believes ”amount a student can learn is primarily related to family background”, 0 if he/she does not; TXDISCIPLINE = 1 if teacher believes ”students not disciplined at home are not likely to accept school discipline”, 0 if he/she does not; TXSTUACHIEVE = 1 if teacher believes ”teachers are limited because home environment influences student achievement”, 0 if he/she does not; TXPARENT = 1 if teacher believes ”if parents would do more for children teacher could do more for students”, 0 if he/she does not; TXHOMEFX = 1 if teacher believes ”teacher cannot do much b/c student motivation/performance depends on home”, 0 if he/she does not; TXABLRANGE = 1 if teacher believes ”teaching is limited by different academic abilities in the same class”, 0 if he/she does not; TXSESRANGE = 1 if teacher believes ”teaching is limited by students with wide range of socio-economic backgrounds”, 0 if he/she does not.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), “Base-year Survey, 2009.”

Table A.3: Pooled OLS Regression - Family Characteristics as Controls

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9
Asian T	0.103*				-0.0257
	(0.0577)				(0.130)
Black T	0.0732	0.272***			
	(0.0483)	(0.0962)			
Hispanic T	0.0115			0.0617	
	(0.0373)			(0.0682)	
White T	-		-0.0241		
	-		(0.0449)		
Male	-0.0243	0.0214	-0.0190	-0.0119	-0.0199
	(0.0159)	(0.0532)	(0.0195)	(0.0422)	(0.0542)
T has STEM Degree	0.0200	0.126*	0.00367	0.0415	0.0129
	(0.0183)	(0.0691)	(0.0233)	(0.0497)	(0.0568)
T's Experience of teaching 9-12 grade yrs.	0.00265***	0.00167	0.00156	0.00152	0.00134
	(0.00100)	(0.00364)	(0.00122)	(0.00290)	(0.00337)
T has Master's or higher degree	0.0128	0.00786	0.00505	0.00567	0.102*
	(0.0159)	(0.0602)	(0.0195)	(0.0481)	(0.0555)
Science FE	0.0720***	0.0637	0.0800***	0.0306	0.0563
	(0.0118)	(0.0520)	(0.0150)	(0.0393)	(0.0495)
Number of Certified Full-time Ts	0.00137	0.0118**	-0.000392	-0.00147	0.00118
	(0.00123)	(0.00575)	(0.00211)	(0.00337)	(0.00395)
Senior T teaches Advanced Courses	-0.0154	-0.0583	-0.00740	-0.000549	-0.0306
	(0.0165)	(0.0715)	(0.0203)	(0.0455)	(0.0556)
Disruption is a Problem	-0.0244	-0.0605	0.00321	-0.113**	-0.0380
	(0.0175)	(0.0640)	(0.0214)	(0.0458)	(0.0561)
Dropout is a Problem	-0.124***	0.118	-0.142***	0.0927*	0.0885
	(0.0180)	(0.0720)	(0.0228)	(0.0517)	(0.0602)
Homework hrs. daily	0.0156	0.0481	-0.0229	0.113	0.0349
	(0.0315)	(0.104)	(0.0381)	(0.0890)	(0.109)
Homework^2 hrs. daily	-0.00230	0.000909	0.00691	-0.0334*	-0.0126
	(0.00616)	(0.0189)	(0.00739)	(0.0171)	(0.0222)
Suburb	0.0470***	0.0460**	0.0399	-0.00151	0.0927
	(0.0178)	(0.0192)	(0.0255)	(0.0593)	(0.0667)
Town	0.0887***	0.0849***	0.0909***	0.0313	0.128
	(0.0238)	(0.0260)	(0.0317)	(0.0993)	(0.110)
Rural	0.107***	0.105***	0.0943***	0.0752	0.120
	(0.0198)	(0.0211)	(0.0284)	(0.0611)	(0.0832)
Family Income	1.04e-6***	1.05e-6***	8.59e-7***	1.63e-6***	-2.72e-7
	(1.56e-7)	(1.29e-7)	(1.94e-7)	(4.15e-7)	(4.87e-7)
Parent 1 has College Degree	0.278***	0.278***	0.301***	0.191***	0.202***
	(0.0201)	(0.0167)	(0.0246)	(0.0655)	(0.0614)
Constant	-0.328***	-0.726***	-0.182**	-0.561***	0.00107
	(0.0512)	(0.200)	(0.0812)	(0.146)	(0.177)
Sample	All	Black	White	Hispanic	Asian
N	15490	1230	9410	2010	1190
adj. R^2	0.034	0.014	0.034	0.027	0.013

Standard errors in parentheses. Standard Errors are clustered at school level. In Column 1, "White" is the reference race. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The number of observation is 15490, which is lower than that used for estimating the baseline results. The reason is that the number of missing observations is higher due to the inclusion of family-related variables in the pooled regression model. Family-related variables: family income variable are in the parent survey. The only result of interest in this table is whether the coefficient estimates change by a large margin. The smaller sample does affect the outcome of the sorting test results presented here. These results are using 94% of the analytical sample.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table A.4: Pooled OLS Regression Results - Teacher Different Race × Other Sex

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9
Teacher Different Race	-0.110***	-0.243**	-0.0214	-0.132	0.0726
	(0.0226)	(0.115)	(0.0583)	(0.0905)	(0.119)
Teacher Different Sex	-0.0375*	-0.190	-0.0406**	-0.0162	0.350
	(0.0202)	(0.126)	(0.0206)	(0.132)	(0.265)
Teacher Different Race × Other Sex	0.00865	0.110	0.0571	0.0553	-0.425
	(0.0307)	(0.135)	(0.0753)	(0.139)	(0.269)
Sample	All	Black	White	Hispanic	Asian
N	16730	1360	10080	2210	1300
adj. R^2	0.014	0.012	0.012	0.010	0.015

Standard errors in parentheses. Standard errors are clustered at school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table A.5: Test for Sorting - Family Income and Parental Educational Attainment

	(1) FAMINCOME	(2) PAR1COL	(3) FAMINCOME	(4) PAR1COL
Non-white Student	17599.9***	0.0680*	22613.3***	0.107**
	(4045.0)	(0.0304)	(4385.6)	(0.0343)
Non-white Teacher	3820.2	0.0624**	10739.5***	0.0843**
	(2762.4)	(0.0210)	(2836.3)	(0.0256)
$\hat{\Omega}$	406.5	-0.0205	-6804.7	-0.0674
	(4120.2)	(0.0300)	(4584.9)	(0.0351)
Constant	45281.4***	0.121***	63780.2***	0.277***
	(2822.1)	(0.0211)	(2667.7)	(0.0251)
N	15490	15490	15490	15490
adj. R^2	0.216	0.172	0.020	0.005

Standard errors in parentheses. Standard Errors are clustered at school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Ω is the coefficient to **Non-white Student×Non-white Teacher**. School × Course fixed effects are included in estimating results in column 1 and 2. School fixed effects are included in estimating results in column 3 and 4. The number of observation is 15490, which is lower than that used for estimating the baseline results. The reason is that the main model does not require family-specific variables because student fixed effects are present in the model. Family-related variables: family income and parental income variable are in the parent survey. Parent survey variables have some non-responses which allows estimation with a smaller sample. The only result of interest in this table is whether the coefficient estimate for Non-white Student × Non-white Teacher is statistically significant. The coefficient size is not of great importance. For this reason, a smaller sample does affect the outcome of the sorting test results presented here. These results are using 94% of the analytical sample.
The two dependent variables FAMINCOME and PAR1COL. FAMINCOME is the family income reported by a parent in the survey. PAR1COL is a binary variable with the value 1 when parent 1 has a college degree and 0 when he/she has not.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), “Base-year Survey, 2009.”

Table A.6: Demographic Mismatch and Self-efficacy

	(1) EF	(2) EF	(3) EF	(4) EF	(5) EF	(6) EF	(7) EF	(8) EF	(9) EF
Other Sex & Same Race	-0.0567**	-0.0573	-0.0503	-0.0456	-0.225	0.0509	-0.643**	0.257	-1.381**
	(0.0271)	(0.0462)	(0.0399)	(0.185)	(0.295)	(0.361)	(0.323)	(0.317)	(0.578)
Same Sex & Other Race	0.0669	0.0598	0.213	0.162	0.0608	0.142	-0.571***	0.103	-0.895*
	(0.0491)	(0.0926)	(0.132)	(0.155)	(0.234)	(0.319)	(0.148)	(0.235)	(0.509)
Other Sex & Other Race	0.0436	-0.0408	0.0564	0.0515	0.0423	0.127	-0.462***	0.220	-0.992*
	(0.0490)	(0.124)	(0.0907)	(0.154)	(0.229)	(0.313)	(0.171)	(0.259)	(0.506)
Sample	All	White Female	White Male	Hispanic Female	Hispanic Male	Black Female	Black Male	Asian Female	Asian Male
N	16370	5100	4980	1150	1050	650	700	650	650
adj. R^2	0.019	0.021	0.019	0.024	0.020	0.034	0.101	0.086	0.033

Standard errors in parentheses. Standard Errors are clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

School × Course fixed effects are included in estimating results in all columns. These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table A.7: Extended Baseline Panel Results - Additional Teacher Survey Instruments as Controls

	(1) ZGPA9	(2) ZGPA9	(3) ZGPA9	(4) ZGPA9	(5) ZGPA9	(6) ZGPA9	(7) ZGPA9	(8) ZGPA9
Other Sex & same Race	-0.0379**	-0.0331*	-0.190**	-0.0194	-0.0488*	-0.0253	-0.437**	-0.758*
	(0.0187)	(0.0190)	(0.0945)	(0.0276)	(0.0280)	(0.155)	(0.182)	(0.409)
Same Sex & other race	0.0231	0.0153	-0.0550	-0.00129	0.0450	0.0829	-0.213	-0.493*
	(0.0391)	(0.0604)	(0.0742)	(0.0495)	(0.0584)	(0.105)	(0.160)	(0.270)
Other race & Other sex	0.0281	0.0702	-0.0524	0.00703	0.0540	0.0896	-0.284*	-0.450
	(0.0396)	(0.0579)	(0.0751)	(0.0533)	(0.0539)	(0.102)	(0.172)	(0.276)
TXFAMILY	0.0109	-0.00414	0.0356	-0.0458*	0.0689**	0.00719	-0.00553	0.219**
	(0.0205)	(0.0251)	(0.0356)	(0.0271)	(0.0292)	(0.0629)	(0.0790)	(0.0947)
TXDISCIPLINE	-0.0101	-0.0128	-0.00513	-0.000779	-0.0190	-0.0245	-0.0335	-0.0521
	(0.0191)	(0.0245)	(0.0302)	(0.0272)	(0.0249)	(0.0526)	(0.0968)	(0.0691)
TXSTUACHIEVE	-0.0262	-0.00922	-0.0557*	-0.00253	-0.0531**	-0.0841	-0.00986	-0.114
	(0.0192)	(0.0233)	(0.0318)	(0.0269)	(0.0264)	(0.0630)	(0.0821)	(0.0765)
TXPARENT	-0.00395	-0.0171	0.0186	-0.0123	0.00165	0.00412	-0.0176	0.0358
	(0.0192)	(0.0234)	(0.0321)	(0.0246)	(0.0265)	(0.0618)	(0.0637)	(0.0706)
TXHOMEFX	-0.00875	-0.0225	0.00847	-0.0255	0.00472	0.0687	0.0700	-0.0598
	(0.0239)	(0.0305)	(0.0395)	(0.0321)	(0.0330)	(0.0684)	(0.0988)	(0.0891)
TXABLRANGE	-0.0227	-0.0378*	-0.000600	-0.0209	-0.0230	0.00118	0.0733	-0.0327
	(0.0173)	(0.0219)	(0.0284)	(0.0237)	(0.0235)	(0.0525)	(0.0622)	(0.0533)
TXSESRANGE	0.0101	0.0308	-0.0220	0.0219	-0.00272	-0.00204	0.0356	-0.0335
	(0.0207)	(0.0251)	(0.0354)	(0.0293)	(0.0288)	(0.0561)	(0.0747)	(0.0996)
Sample	All	White	Non-white	Female	Male	Hispanic	Black	Asian
N	16370	10080	6650	8430	8300	2210	1360	1290
adj. R^2	0.017	0.012	0.015	0.019	0.019	0.010	0.017	0.055

Standard errors in parentheses. Standard Errors are clustered at school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
School × Course fixed effects are included in estimating results in all columns. These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10. Additional variables: TXFAMILY = 1 if teacher believes "amount a student can learn is primarily related to family background", 0 if he/she does not; TXDISCIPLINE = 1 if teacher believes "students not disciplined at home are not likely to accept school discipline", 0 if he/she does not; TXSTUACHIEVE = 1 if teacher believes "teachers are limited because home environment influences student achievement", 0 if he/she does not; TXPARENT = 1 if teacher believes "if parents would do more for children teacher could do more for students", 0 if he/she does not; TXHOMEFX = 1 if teacher believes "teacher cannot do much b/c student motivation/performance depends on home", 0 if he/she does not; TXABLRANGE = 1 if teacher believes "teaching is limited by different academic abilities in the same class", 0 if he/she does not; TXSESRANGE = 1 if teacher believes "teaching is limited by students with wide range of socio-economic backgrounds", 0 if he/she does not.

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."

Table A.8: Falsification Test: 8th-grade GPA and Future Demographic Mismatch

	(1) ZG8	(2) ZG8	(3) ZG8	(4) ZG8	(5) ZG8	(6) ZG8	(7) ZG8	(8) ZG8	(9) ZG8
Other Sex & same Race	-0.0198	-0.0283	0.0117	0.0739	-0.447	-0.456	-0.732	-0.0162	-0.207
	(0.0228)	(0.0302)	(0.0343)	(0.284)	(0.424)	(0.514)	(0.424)	(0.253)	(0.642)
Other Race & same sex	0.0123	0.0938	-0.0971	-0.246	-0.280	0.0000561	-0.130	-0.0198	-0.249
	(0.0415)	(0.0638)	(0.112)	(0.198)	(0.208)	(0.196)	(0.209)	(0.218)	(0.186)
Other Sex & other Race	-0.0230	-0.161	0.0524	-0.276	-0.249	0.0433	-0.242	-0.140	-0.303
	(0.0460)	(0.9370)	(0.0883)	(0.226)	(0.195)	(0.229)	(0.199)	(0.218)	(0.187)
Science FE	-0.0232*	0.0430	0.0238	-0.119	-0.1000	-0.207*	-0.262	-0.0117	-0.113*
	(0.0128)	(0.0272)	(0.0284)	(0.0735)	(0.0717)	(0.105)	(0.9317)	(0.0811)	(0.0592)
Sample	All	White Female	White Male	Hispanic Female	Hispanic Male	Black Female	Black Male	Asian Female	Asian Male
N	11940	3530	3540	790	770	470	520	520	470
adj. R^2	0.048	0.058	0.049	0.045	0.042	0.048	0.035	0.0332	0.063

Standard errors in parentheses. Standard Errors are clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

School × Course fixed effects are included in estimating results in all columns. These results are estimated with the same set of control variables in the regression equation as those in Tables 9 and 10. **The samples exclude those students who are in schools that includes an 8th-grade.**

Data Source: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09/16), "Base-year Survey, 2009."