An *Older* College Professor Like Me

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Abstract

Past research shows that students' educational outcomes improve when their race is the same as their teachers' race. One explanation for this finding is the Role Model effect: instructors increase same-race students' motivation by updating their beliefs on returns to education and providing an example of a career/educational path that the same-race students can imitate. This paper empirically evaluates the importance of the Role Model effect under the premise that this channel is more applicable to students significantly younger than their professors. Using administrative data from a Carnegie R1 classified university where an ample share of students are older than the traditional college age and focusing on a subsample of required classes that eliminate the possibility of strategic instructor choice, we show that students whose races are the same as their professors earn higher grades in their courses, but only if they are considerably younger than their professors. Specifically, young race-matched students' course grades increase by about 0.1-0.2 on a 4.0 scale. Benefits from student-teacher race matches do not accrue to older students. We provide evidence suggesting our results are not driven by students' strategic course-taking behavior, such as signing up for easy classes or preferred instructors, delaying courses, or major switching in a calculated fashion. The race-match effects start early in the semester and persist in the long run until graduation. We do not find any race-match effect for either young or old STEM students who are high achieving and already highly motivated. The highest quality, high-value-added instructors improve all students' grades regardless of race and age.

Keywords: Student-teacher racial congruence; race-match; role models; college; course grades

JEL Codes: I23, J15, J14

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1. Introduction

A large number of past studies document an improvement in students' short- and long-term educational outcomes when their races match their teachers' races. For example, Delhommer (2022), Harbatkin (2021), Egalite, Kisida, Winters (2015), and Dee (2004) argue that having a same-race teacher increases a student's short-term course outcomes, such as their course grades and their performance in standardized tests, at the K-12 level. In their study of community colleges, Fairlie, Hoffmann, and Oreopoulos (2014) show that the race-match effects extend to higher education. Others, such as Kofoed and mcGovney (2019) and Price (2010), suggest that student-teacher race match influences students' major and occupation choices in the future. Many of these papers report that the benefits from a race-matched instructor mostly amass to the minority, especially Black, students, while some show that White students also enjoy improved outcomes when matched with White teachers.[1] These effects are significant in US education, where nearly half of White adults have a college degree, compared to less than a third of Black adults (Nichols and Schak 2017). A possible contributor to the educational achievement disparities between racial/ethnic minorities and others in the US could be the marked lack of diversity among educators (Dee 2005).[2]

In this literature, the *Role Model Effect* is one highly-cited mechanism through which same-race instructors are thought to improve students' educational outcomes.[3] Under this

[1] There is an equally extensive literature that investigates the impact of student-teacher gender-matches. Examples include Lim and Meer (2017) who show that female middle school students in South Korea earn higher scores in standardized tests if their teachers are also female. Lim and Meer (2020) in their follow-up work present evidence that same-sex teachers improve long-term outcomes when the students are in high school. Carrell, Page, and West (2010) and Bettinger and Long (2005) show that having a female instructor increases performance of female students in science and math classes in college and their tendency to obtain a STEM degree. Evidence presented by Hoffmann and Oreopoulos (2009) and Griffith (2014) suggest that a same-sex instructor increases average grade performance of college students.

[2] According to the National Center for Education Statistics, in 2017, about 80% of K-12 teachers in the US were White, compared with just 48% of students in public elementary and secondary schools. Similarly, on college campuses, about three out of every four faculty members are White, compared to just 56% of students.

[3] Researchers suggested that other mechanisms may be at work as well. For example, teachers of a certain race could be more effective in teaching students of that race because they may be using a "culturally-relevant pedagogy" and may be able to communicate the course material better (Delhommer 2022). A line of research highlights the importance of teacher biases in favor of her/his group (endophilia) or against other groups (exophobia) (Feld, Salamanca, and Hamermesh 2016; van Ewijk 2011; Dee 2005). A third mechanism could be through teachers' expectations. For example, Gershenson, Holt, and Papageorge (2016) show that non-Black teachers of Black

hypothesis, a same-race instructor increases the student's motivation in the class and the subject area in general. This is because the student views the instructor as a successful model that can be emulated and updates her/his beliefs on the returns to education or training in that field (Egalite and Kisida 2018).[4] Alternatively, teachers with the same ethnic/racial background as their students may be better informed about the career opportunities and challenges particular to that demographic group, consequently more effectively guiding their students to overcome them.

In this paper, we evaluate the importance of the Role Model Effect based on the premise that this mechanism is more applicable to students younger than their professors. For example, an older teacher can inform younger students more effectively because the career/educational path she/he took in the past serves as a blueprint, and it can be mimicked by young students in the future. Thanks to her/his experience, such a professor can more easily anticipate the difficulties the young student may face in a specific stage of life and assist the student in navigating past them. On the other hand, a younger professor is possibly unfamiliar with the hardships that older students could encounter at a stage in their life cycle that she/he has not experienced yet. As a result, it may be more difficult for this young professor to guide her/his older students to follow a trajectory similar to hers/his. In addition, the updating beliefs about the returns to education channel may be less relevant for the old student-young professor pairings. This is because the human capital investment the young professor undertook in the past (when she/he was even younger) may not be available or applicable to the older student. Alternatively, the returns to human capital investments at earlier versus later stages of life could be different (Kim and Baker 2015).

To test whether the benefits of student-teacher race matches apply to younger versus older students, one needs to observe variations in the age of the students relative to their instructor's age. This is not feasible in most K-12 settings, where students are typically much younger than their teachers. Similarly, in most colleges, the student body comprises young individuals, preventing researchers from estimating differential race-match effects by age with precision due to the lack of power. To overcome this challenge, we partnered with a public

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students have significantly lower expectations of them than Black teachers, and this may influence the students' performance and future course-taking behavior.

[4] Others besides the instructor-of-record in a class can serve as a role model for the students too. For example, Porter and Serra (2020) report that the female students at Southern Methodist University are more likely to major in economics if they are exposed to successful women with economics degrees from the same university.

university where a notable, though still a minority, share of the student body is older than the traditional college age. Specifically, in this university, the proportion of undergraduate students that are 25 or older is 23%. In comparison, in other four-year colleges similar to ours (doctoral degree-granting institutions), according to the statistics obtained from IPEDS, the average share of students 25 and over is 15%.[5] Our data set is constructed using students' transcript information and the demographic attributes, including race/ethnicity and birth date, of students and their instructors.

Unlike those in colleges that train officers for the military, students in the university with which we work (and other civilian universities) have the freedom to choose their classes and their instructors.[6] Therefore, a student may strategically select her/his preferred instructor based on race or other characteristics. To avoid biases that may arise due to such non-random sorting of students into classes and instructors, we focus on a subsample of classes, to which we refer *Must-Take classes*, i.e., courses that are required by a student's academic program of study without any alternatives and taught by only one instructor in a semester. Strategic instructor selection is not an issue in their Must-Take classes because the students must complete these required classes to obtain a degree in their academic majors. This prevents them from substituting the Must-Take class with another one. Furthermore, our restriction of one instructor eliminates the possibility of choosing between professors that deliver the same course.[7]

In our estimation, we use the variation in the races and ages of students who are otherwise observationally identical and who take the same Must-Take course in the same classroom from the same professor in the same semester due to their academic major's requirements. Consider four hypothetical students in that class. Two of these students have the same race as the instructor (one older and one younger), while the other two are of a different race (again, one older and one younger). We are most interested in two comparisons between these four students: i-) the young race-matched student versus the young student of a different

[5] In our university, the shares of students aged 25-40 and 40+ are about 18% and 5%, respectively. In other comparison universities, the same shares are 12% and 3%.

[6] In US Military Academy and in US Air Force Academy, student cadets are randomly assigned to classes/instructors (Kofoed and mcGovney 2019; Carrell, Page, and West 2010).

[7] On the other hand, the choices students are provided in their other courses, such as electives or the required courses taught by multiple different instructors, are aplenty. We refer to these as *May-Take Classes*. In our empirical analysis, we provide evidence for strategic instructor selection by the students based on their and instructors' demographic attributes in May-Take classes.

race, and ii-) the comparison between the old race-matched student and the young race-matched student. Importantly, our regressions include student and class (course-term-section) fixed effects.[8] The student fixed effects isolate the potentially confounding impact of time-invariant unobservables, such as aptitude/ability, college preparedness, and familial resources. The inclusion of class fixed effects enables us to compare students who are in the same class and exposed to the same course material, delivery, and tests.

Consistent with previous findings, our results show that younger students who share the same race as the instructor are 2% more likely to pass the class compared to their counterparts who are also young but of a different race. The race match effect on young students' final grades is 0.12 (out of a 4.0 scale), or about 4% relative to the average final grade. We find no impact of a same-race professor on the probability that a student completes the class. In contrast, the effects are very different for older students in the class. Those about the same age or older than their instructor do not benefit from having a same-race instructor. The offsetting, negative effects are particularly pronounced for those within five years of their instructor's age. These findings support the idea that the role model channel could be the primary mechanism through which same-race instructors improve the academic achievement of their students.

A student may postpone taking the required courses for a few semesters until her/his preferred professor delivers them. This course of action is costly and therefore unlikely because delaying the completion of a required course also delays the student's graduation. Nevertheless, if students partake in such strategic delaying of required courses, our results could be biased. We investigate this conjecture and find that, compared to their counterparts who take the courses on time, students who delay taking classes in the above-mentioned calculated fashion are no more or less likely to get matched with professors with favorable attributes regarding age and race. We also show that our main findings are robust to using the subset of classes required by students' majors and taught by the same professor in at least two and at least three consecutive semesters. In another set of robustness analyses, we show that our estimates are not an artifact of students' academic major switches. For example, we show that the estimates obtained from the subset of students who never switched majors are similar to our baseline estimates.

[8] That is, our regressions include a separate dummy for each course (such as Principles of Microeconomics) taught by a particular instructor (Professor X) in a certain classroom and time (Tuesdays-Thursdays 9 am to 10 am) in a specific semester (Spring 2015).

We conducted several extension analyses. For example, we show that the race-match effects for the younger, but not older, students begin early in the semester. Specifically, these students' midterm grades increase when their instructor's race is the same as theirs. In addition, having a same-race and older professor improves downstream outcomes. Students who take a class from such professors are less likely to repeat that class in the future. We also provide evidence that older same-race professors increase the probability that a student will graduate on time, i.e., in four years. In other analyses, we show that our results are primarily driven by students in non-STEM (Science, Technology, Engineering, and Mathematics) programs. We offer evidence that younger students in non-STEM fields, such as art, humanities, and business, obtain higher course grades when they take classes from same-race professors, while older students in their classes do not. For both young and old students in STEM fields, we do not find any benefit that arises due to racial congruence. This difference could be observed because students in STEM fields are already highly motivated and high achieving, and the professors cannot improve/motivate them significantly. Finally, we explored the role of teacher quality in race-match effects and the role model channel. We show that student-teacher racial congruence benefits the young, but not old, students in classes taught by professors whose value-added to student grades (à la Chetty, Friedman, and Rockoff 2014a) is low. In striking contrast, we find no race-match effects in classes delivered by the highest value-adding professors. This finding implies that the highest quality teachers may motivate and improve all students' grades regardless of race or age.

In the next section of our paper, we discuss our data and present details about our empirical framework and identification strategy. This discussion is followed by our baseline results, robustness analyses, and extensions. In the paper's final section, we summarize our findings, discuss their implications, and provide concluding remarks.

2. Data and Empirical Framework

Our data are obtained from administrative student records from a public university in the southern US. The university grants bachelor's, master's, and doctoral degrees and has a diverse student body of about 15,000 enrolled students per year from all US states and various countries. The student records include information on students' final and midterm grades for each class they take at this institution and their academic major and seniority. In addition, we have access to the personal attributes (age, gender, and ethnic background) of each student and the instructor of record of each class.[9] We focus on American undergraduate students enrolled in courses from 2012-2013 through 2017-2018 academic years, including summer terms.[10] In this period, about 38,000 unique undergraduate students (2,300 unique instructors) took (taught) at least one class at this university.

Our main estimation equation, which follows the specifications in past work on the impact of student-teacher demographic congruence on the student's class outcomes (Delhommer 2022; Harbatkin 2021; Egalite and Kisida 2018; Fairlie, Hoffmann, Oreopoulos 2014; Hoffmann and Oreopoulos 2009), is depicted below:

$$(1) \qquad Y_{ikstr} = \beta_1 Race\ Match_{ikst} + \beta_2 Race\ Match_{ikst} \times Non\ Role\ Model\ Instructor_{ikst} + \beta_3 Non\ Role\ Model\ Instructor_{ikst} + \gamma X_{it} + \mu_i + \delta_{kst} + \theta_{kr} + \varepsilon_{ikstr},$$

where students, courses, sections, and academic terms are indexed by i, k, s, and t, respectively. A class is a course section taught in a particular semester (kst). Thus, the unit of observation is a student×class. Ethnic/racial groups (White, Black, Asian, Hispanic) are represented by r.

In our baseline specification, we consider three outcome variables (*Y*). The first indicates whether the student completes the class, i.e., she/he does not withdraw from it. The other outcomes are based on the student's final grade, which we can observe only when a student completes the class. These variables stand for whether the student passes the course (earns a D or higher) and the numeric final grade (A=4, B=3, C=2, D=1, and F=0).

The variables of interest in equation (1) are *Race Matched Instructor* and its interaction with *Non-Role-Model Instructor*. The *Race Matched Instructor* dummy takes the value of one when the races/ethnicities of the student and her/his teacher are the same. We constructed the

[9] In the transcript data, instructor ethnicity categories are: American Indian/Alaska Native, Asian, Black/African American, Hispanic/Latino, Not Specified, Two or More Races, and White. Student ethnicity categories are: American Indian/Alaska Native, Asian, Black/African American, Hispanic/Latino, Native Hawaiian/Other Pacific Islander, Not Specified, Two or More Races, and White. In our analysis, we group instructors and students into the following categories: Black/African American ("Black"); White; Asian; Hispanic/Latino ("Hispanic"); and all others ("Other").

[10] The University's academic year consists of a Fall, Spring, and Summer term. We limit the most recent year of data in our sample to the 2017-2018 academic year to avoid potentially confounding effects of: i-) a major reorganization of the University's academic structure which occurred during the 2018-2019 academic year; and ii-) the COVID-19 pandemic, which began during the 2019-2020 academic year.

Non-Role-Model Instructor variable to operationalize the idea that for an instructor to be a role model for a student, she/he must be significantly older than the student. This variable indicates whether the instructor is "too young" to be a role model for the student. More specifically, *Non-Role-Model Instructor* is equal to one if the student is about the same age as her/his teacher, i.e., within ten years of an age difference, or older than the teacher.[11] Consider, for example, three students, X, Y, and Z, aged 50, 35, and 20, who take the same class from a 40-year-old professor. In this case, the *Non-Role-Model Instructor* variable takes the value of one for student X, as the professor is younger than her, indicating the professor is unlikely to be a role model for X. Similarly, it is equal to one for student Y because the age difference between the professor and student is only 5, i.e., they are of similar age. However, the *Non-Role-Model Instructor* variable is zero for student Z since she is twenty years younger than her professor, who is old enough to be her role model.[12] Importantly, this and the *Race Matched Instructor* variable vary within a student. For example, for a 40-year-old White student, *Race Matched Instructor* and *Non-Role-Model Instructor* will be equal to one when taking a class taught by a 40-year-old White professor, while both variables will be equal to zero in a different class in which the professor is a 55-year-old Black person.

In our university, we can observe students like X, Y, and Z from the hypothetical example. Figure 1 displays the distributions of student and instructor ages. The orange (purple) bars portray the density of the students (instructors). Each bar represents one single age. Unlike other colleges, which typically have limited variety in the age of enrolled students, students in our sample range from 16 to 72. Instructors' age also displays a wide range (21 to 79). Figure 1 shows that the ages of a small but ample share of students and teachers overlap, allowing us to estimate equation (1). Note that there is little variation in the *Non-Role-Model Instructor* variable within the classes of the very young or very old instructors because of the age distributions of students and instructors. For example, the *Non-Role-Model Instructor* variable almost always equals one or zero in courses delivered by instructors under 30 or over 50. Thus, our estimates

[11] Later in the paper, we show that our results are not sensitive to using alternative age thresholds.

[12] To be clear, we classify whether or not the instructor is the student's role model based only on the *relative* ages of the student and instructor. That is, it is possible for an old student who is, say, 45 years old, to view their instructors over the age of 55 as a role model. Under our conjecture, the 45 year old student is more likely to view the 55 year old instructor as their role model compared to younger instructors. It is possible that very old students reach a point where they do not look up to anyone as a role model, since they already had important mentors in their younger years. However, in our analysis we do not consider role model effects based on any absolute age threshold.

are mainly driven by classes taught by instructors in their 30s and 40s, where there is within-classroom variation in the *Non-Role-Model Instructor* variable. Specifically, in classes led by instructors between the ages of 30-39, the share of students who are about the same age as or older than the instructor is 34% (N=1,295). For instructors aged 40-49 and 50-59, the share is 7% and 2% (N=1,927 and 1,391), respectively.

The coefficient on *Race Matched Instructor* (β_1) in equation (1) informs us about the impact on course outcomes of racial matches between instructors and students for whom the role model effect is relevant, i.e., students significantly younger than their instructor. We expect β_1 to be positive and significant, given the results of numerous previous studies (Delhommer 2022; Harbatkin 2021; Egalite and Kisida 2018; Fairlie, Hoffmann, and Oreopoulos 2014; Dee 2004). The coefficient of the interaction between *Race Matched* and *Non-Role-Model Instructor* (β_2) captures the differential impact of racial matches for student-teacher pairings if the role model effect does not apply. A negative β_2 would indicate the importance of the role model effect, while a zero or positive β_2 speaks to the significance of other mechanisms, such as teachers' expectations of their students or improved interpersonal connections between racially matched students and teachers.

The vector *X* in equation (1) includes time-varying student characteristics, such as their seniority (Freshman, Sophomore, Junior, or Senior, with Senior being the comparison category) and age in years.[13] Student fixed effects (μ_i) in the regressions isolate the time-invariant student attributes, like family resources, inherent student ability, level of college preparedness, and other aspects of student aptitude. We also control for class fixed effects (δ_{kst}) in the regressions. Having class fixed effects in the regressions allows us to compare the outcomes of students who take the same class, i.e., who were exposed to the same instructor, course materials, and course policies, such as grading schemes, and, importantly, who took the same tests.[14] Finally, following Hoffmann and Oreopoulos (2009), we include course-by-race dummies (θ_{kr}) in equation (1). These indicators account for the variation that may arise due to the possibility that courses where students of a particular race tend to excel in also tend to be taught by instructors of

[13] Time-invariant student characteristics and all instructor characteristics are excluded from the vector *X* since we condition on student fixed effects (represented by μ) and class fixed effects (represented by δ) in equation (1).

[14] Denning et al. (2022) documents the prevalence of grade inflation in US colleges in recent years.

that race. For example, in our sample, students who take Intermediate German classes and the instructors of these classes are overwhelmingly White. At the same time, White students taking German may be more likely to excel in the course compared to minority students. An alternative example could be a course in Black studies where Black students may have an inherent advantage over students of other races and, possibly, are more likely to be matched with Black instructors. Omitting the course-by-race fixed effects from regressions could cause our key parameters to pick up on these effects, which are specific to racial trends in course enrollment and instructor assignment, rather than effects due to student-instructor congruence. The error term is denoted by ε. We cluster the standard errors at the class level.

2.1. Identification Issues

2.1.1. Strategic Course Selection Based on Instructor Characteristics

During their college education, students take many courses to complete a degree in their academic programs. Typically, the departments, colleges, and the university require the completion of specific classes and some electives.[15] Students have abundant options in the choice of their instructors in their elective courses as well as the required courses that multiple faculty members teach in different sections. The possibility that students strategically select themselves into classes based on the instructor's attributes is one of the biggest threats to identifying causal effects in our context. For example, if high-achieving students are systematically more likely to choose classes taught by same-race instructors, our estimate of the race-match effect could be biased.

To address the concern of strategic choice of classes by students, we categorize classes into two groups: "*Must-Take*" and "*May-Take,*" and we focus on the former in our estimation. The classification is described in Figure 2. The Must-Take classes of a student satisfy the following criteria: i-) the student has to take this particular course to obtain her/his degree, and there are no alternatives for that course in her/his program of study; ii-) the course must be

[15] Our partner university requires students to take one or two courses in composition, science, math, humanities, history, and social sciences. In addition, all students must complete one writing-intensive and one speaking-intensive course as well as a program-specific capstone class. Students have to complete approximately 120-130 credit hours to obtain their degree. Besides the university requirements, colleges and departments specify as necessary several required and elective courses. The requisites for a degree vary from one department to another. Some programs allow much leeway to students in their choice of courses, while others are highly structured.

offered by only one instructor during the semester, in one or multiple sections.[16] The May-Take classes are the other courses students can take to satisfy their degree requirements.[17] In other words, May-Take classes are either elective or required by the student's academic program but delivered by multiple instructors in a semester.

The May-Take classes are expected to be subject to strategic selection by students. To verify this, we estimate regressions of the following form over the sample of May-Take classes:

$$(2) \qquad Instructor\ Attribute_{kst} = \beta Avg.Student\ Attribute_{kst} + \delta_{kt} + u_{kst},$$

where the unit of observation is a class (i.e., course-section-term – *kst*). The outcomes are the characteristics of the instructors who deliver the classes. We use as the outcome the race/ethnicity of the instructor (dummies for whether the instructor is Black, White, Asian, or Hispanic), the average grades assigned by the instructor of this class to her/his students of a particular race/ethnicity in the past semesters, and instructor's age. On the right-hand side of equation (2), we include the average demographic characteristics of the students in the class. If students with a particular demographic attribute systematically register for instructors with the same specific features, then the estimate of β in equation (2) should be positive. Such a result would be indicative of the selection of students into instructors. On the contrary, if β is zero, this

[16] We hand-collected information on the required courses for each of the 165 majors/academic programs from the University's undergraduate bulletins (available on the web starting with the 2012-2013 academic year). The distribution of majors at the University is broadly consistent with the typical US university. According to the National Center for Education Statistics, the most common categories of conferred degrees by postsecondary US institutions during 2019-2020 were business (19%), health professions and related programs (13%), and social sciences and history (8%). In our data, the share of students in business, health, and social sciences/history programs are 17%, 18%, and 12%, respectively. We include the 2012-2013 academic year as the first year of our sample period since this is the earliest year which an online academic bulletin is available. The average number of required courses per major is about 21. In some years, majors' required courses change slightly. In our analysis, we only include the courses that are required every year within each academic plan.

[17] As an example, consider the economics program, which requires the completion of Intermediate Microeconomics and Intermediate Macroeconomics courses as well as one field course in either Labor Economics or International Trade. Suppose the Intermediate Microeconomics course is taught by only one professor while the Intermediate Macroeconomics is delivered by two different instructors in two separate sections. In this case, Intermediate Microeconomics is classified as a Must-Take class for students majoring in Economics. On the contrary, we categorize Intermediate Macroeconomics as a May-Take class for economics majors even though it is a requirement for the degree. This is because students can pick and choose their professors for the Intermediate Macro, and consequently, they do not have to be with a particular professor. Finally, we group Labor Economics and International Trade classes as May-Take for economics majors as well since the economics students can opt in or out of one of them. Following up with the same example, suppose that the finance program requires the completion of any one economics course. Then, for finance majors, these economics courses are categorized as May-Take.

would provide evidence against selection. Note that we include course×term fixed effects (δ_{kt}) in equation (2). That is, the estimation of equation (2) involves the comparison of instructors of two (or more) separate sections of the same course in the same semester.[18]

Results from equation (2) are presented in Table 1. In Panel A, outcomes are indicators for the instructor's race, and the right-hand side variable is the share of students in the class of the same race. Columns 1 through 3 show that the coefficients on the share of Black, White, and Asian students in the class are positive and significant. This means that Black, White, and Asian students are more likely to be concentrated in classes led by same-race instructors in May-Take classes. We did not find a significant concentration of Hispanic students in May-Take classes led by Hispanic instructors (column 4). In Panel B of Table 1, the outcomes are the average grades assigned by the instructor to students of a particular race/ethnicity in her/his past classes. This panel provides evidence for selecting classes based on instructors' past grades. For example, White and Asian students are more likely to sign up for their May-Take courses with teachers with whom other White and Asian students were able to obtain higher grades in the past, respectively (columns 2 and 3).[19] Panel C presents the results from regressions where the outcomes are based on the instructor's age. Since age, unlike race, is continuous, we include a set of dummy variables encompassing all student ages in each regression. The omitted category is the share of students in the class under 20 years old. The results in Panel C show that younger students are typically clustered in May-Take classes taught by younger teachers (under 40). The results in Table 1 suggest that students select themselves into the courses or sections of classes led by instructors with favorable characteristics if they can do so.

A class is categorized as May-Take either because it is an elective course (i.e., the student can choose among a menu of courses) or because it is required by the student's major but offered by multiple professors in the same semester. We investigated whether students engage in strategic instructor selection in their required classes offered by different professors in the same semester (required May-Take classes). The results in Appendix Table 1 show that Black and

[18] We ran equation (2) with separate course (k) and term (t) fixed effects instead of course×term (kt) fixed effects. In this specification, the variation comes from not only between sections of a course in an academic term but also between the terms. The estimates obtained from these regressions generated results that are similar to those presented in Table 1.

[19] We re-estimated the regressions in Panels A and B using the shares of students in all race/ethnicity categories (omitted category was Whites) and obtained results similar to those in Table 1. For example, minority students were more (less) likely to be concentrated in May-Take classes taught by Black and Asian (White) instructors.

White students are concentrated in the sections of the required courses taught by Black and White instructors, respectively. Asian and Hispanic students are more likely to register in sections of a required course taught by instructors who assigned higher grades to Asians and Hispanics in the past. The evidence in Appendix Table 1 indicates that students tend to engage in deliberate instructor choice even in their required courses if multiple professors teach these courses in one semester.

In contrast to their May-Take classes, the strategic instructor selection by students is a non-issue for their Must-Take classes, i.e., those required by the student's program of study and taught by only one professor in a semester. This is because all observations in this sample pertain to the *students who had to be in the class*, and consequently, they could not pick and choose particular instructors. Our Must-Take classes sample includes 11,200 unique students and 727 unique instructors in about 6,000 classes. Eighty-eight percent of these classes are offered in one section in a semester. Most of the Must-Take classes are at the 300- and 400-levels.

Summary statistics displayed in column 1 of Table 2 show that students in this sample are predominantly White (69%) or Black (25%), and the majority of them are female (62%). The typical student is 23 years old. Instructors of the Must-Take classes are also predominantly White (86%). The second and third most common instructor ethnicities are Asian (9%) and Black (3%). The average instructor age is about 47 years. Half of the professors teaching these classes are female. On average, there are about 12 students for whom the class is Must-Take in our analysis.[20] Typically, two out of these twelve students are roughly the same age as their instructor or older, while the rest are significantly younger than their instructor. About 60% of a class has the same race/ethnicity as the instructor.

Columns 2 and 3 of Table 2 show variable means for subsamples of Must-Take classes with *Race Matched Instructor* equal to one and zero, respectively. The probability of completing the class and the probability of earning a passing grade are high and about the same in these subsamples. However, the numeric grades are higher for race-matched students. Some characteristics of students and instructors, such as their age and student seniority, are balanced. For example, the average ages of students and teachers in both subsamples are 23 and 47, respectively. A critical difference between racially matched students and others is that most race

[20] There are an average of 19 *total* students in these classes, including Must-Take students as well as those students for whom the class is a May-Take.

matches occur for Whites. This is because most of the Must-Take classes are delivered by White professors, and most of the students are White.

2.1.2. Strategic Delays of Taking a Must-Take Course

Although students cannot choose their instructors in their Must-Take classes within a particular semester, they may delay taking a Must-Take class to sign up with their instructor of choice. This is possible even though this course of action is costly as it will delay the student's graduation. During our sample period, about 68% of instructors in a semester taught a class that she/he taught in the previous Fall or Spring semester. This indicates that while much of the professors' course offerings are consistent over time, a student can wait one or more semesters to take a course with the hopes (or with the knowledge) that her/his preferred instructor will teach the course in the future.

We examine whether students postpone taking a course by comparing the actual time they took a Must-Take class and the time *recommended* by the university/academic unit. The sources of the recommended times are the semester-by-semester guides of each major published in the academic bulletins.[21] We obtained from this source the year (freshman, sophomore, junior, or senior) during which the university advises the student to enroll in a particular course. The comparison of the recommended to the actual time reveals that 50% of the Must-Take classes are taken in the year same as the recommended year. We also found that about 42% (8%) of the time, a student registered for a class later (earlier) than suggested. The typical delay in our sample period is one year.

We investigated whether students strategically time their Must-Take courses to get a race-matched instructor by estimating equation (1) using outcomes *On Time Course Taking* and *Delayed Course Taking*. The former (latter) takes the value of one if the student has registered for the course in (after) the year that the university recommends. The results presented in Table 3 show no statistically significant relationship between student-instructor race matches and course timing. This finding indicates that students who take the course on time, as recommended by the

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[21] For example, for an economics degree, the recommended courses in the freshman year are two particular English composition courses, two foreign language courses, one of the two specified history courses, two specific basic mathematics courses, an arts course to be chosen from a list of four, an unrestricted elective, and three principles level economics courses.

university, are no more or less likely to get a race-matched professor than their counterparts who delay taking a Must-Take course.[22]

We additionally tested whether students engage in intertemporal substitution in their Must-Take classes to be matched with a teacher with preferred attributes by estimating over this sample a series of regressions outlined by the following equation:

$$(3) \qquad Instructor\ Attribute_{kst} = \beta Avg.Student\ Attribute_{kst} + \delta_k + \tau_t + u_{kst},$$

Equation (3) is identical to equation (2) except for the fixed effects. In equation (3), instead of course×term fixed effects, we include course fixed effects (δ_k). As a result, the variation comes from the same courses taught in different semesters. Equation (3) also includes semester fixed effects (τ_t) to isolate the influence of the unobserved events that affected all classes in the same way.[23]

Results obtained from equation (3) are given in Table 4. Panel A (C) shows that in their Must-Take classes, students of a specific race/ethnicity (age group) do not select classes led by instructors from the same ethnic/racial background (of a certain age). Regressions presented in Panel B indicate that students of a certain racial group do not sign up for required classes from instructors who have assigned high grades to students from the same racial group in the past.[24] The null results in Table 4 provide additional evidence that students do not strategically select themselves into their preferred professors in the Must-Take courses by delaying taking them.[25]

2.1.3. Do High-Achieving Students Prefer Instructors of the Same Race?

Do high-ability students tend to choose same-race instructors? If this is the case, and high-ability students earn high grades in their Must-Take classes, our estimates in equation (1) could differ from the true effects. We test for this by running the regression equation below:

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[22] We examined whether the delays are driven by the students who transferred to our university from another. Omitting the transfer students from this analysis does not change the inference. Results are available upon request.

[23] We cannot estimate this regression with course×term fixed effects because close to 90% of the Must-Take classes are offered only in one section.

[24] We obtain similar results when we included all race/ethnicity categories in these regressions (excluding %White students variable from the regression).

[25] We obtain similar results if we run the same regressions at the student-class level.

$$(4) \qquad \bar{Y}_{it} = \beta_1 Cumulative\ Past\ GPA_{it} + \mu_i + \tau_t + u_{it},$$

where the unit of observation is a student×term. The outcomes are $\overline{Race\ Match}$ and $\overline{Non\ Role\ Model\ Instructor}$. The first outcome, $\overline{Race\ Match}$ represents the share of the student's classes in term t in which the student and the instructor have the same race. Similarly, $\overline{Non\ Role\ Model\ Instructor}$ is the share of the student's classes in term t where the instructor is about the same age or younger than the student. *Cumulative Past GPA* is the student's cumulative GPA from her/his past courses taken at the University as of the beginning of term t. Results reported in Table 5 show essentially zero correlation between a student's past GPA and the share of classes in which she/he and the instructor have the same race or age.

3. Results

3.1. Baseline Results: The Impact of Race Match on Course Grades

We present the results of our main specification, equation (1), in Table 6. The unit of observation is a student×class, and the left-hand side variables are the student outcomes from the class. In addition to the variables listed in the table, right-hand side variables in the regressions include student and class fixed effects as well as course×race dummies. The sample is composed of observations from students' Must-Take classes. Standard errors are clustered at the class level.

In column 1, the coefficient of the *Race Match* variable is 0.007 and statistically insignificant, which indicates that students whose ethnic/racial backgrounds are the same as their instructor are not more or less likely to complete the course compared to their counterparts in the same class but identify with a different racial/ethnic group than their professor. Regressions in columns 2-3 use the sample of students who complete the course, i.e., obtain a final grade. Column 2 shows that student-teacher racial congruence increases the probability of passing the course (getting a D or higher) by 1.5 percentage points. The estimates in column 3 suggest that the match of the race/ethnicity of students and professors positively influences the student's GPA. For example, taking a class from a same-race instructor increases the student's final course grade by 0.12 (a 4% increase relative to the mean of the outcomes). These magnitudes are generally consistent with, or perhaps slightly greater than, those found by other recent studies.[26]

[26] Using data on middle and high school students, Harbatkin (2021) shows that numeric grades tend to be about 0.02 higher when student-teacher race matches occur.

The other variable of interest in Table 6 is the interaction of *Race Matched* and *Non-Role-Model Instructor*. Recall that the *Non-Role-Model* variable takes the value of one if the student is about the same age as her/his instructor (i.e., the difference between the instructor's age and the student's age is less than or equal to 10) or older than her/his instructor. In other words, this dummy indicates that the instructor is too young relative to the student for the role model channel to operate. The coefficient of the interaction term describes the differential impact of racial/ethnic matches between students and teachers for the older students for whom the instructor is not a role model. The sum of the coefficients of *Race Matched Instructor* and *Race Matched×Non-Role-Model Instructor* shows the net effect of race congruence for this group of students.

In Table 6, the coefficients of *Race Matched×Non-Role-Model Instructor* are negative in all regressions and statistically significant at conventional levels in two out of three cases. This finding implies that the net effect of race match for older students, for whom the instructor is too young to be a role model, is smaller than that for students significantly younger than the teacher. For example, column 3 shows that the impact of race matches on older students' final grades is 0.033 (0.119 – 0.086), and this estimate is statistically insignificant with a p-value of 0.33 (presented at the bottom of Table 6). On the other hand, race matches increase younger students' final grades by 0.119. Results in column 2 of Table 6 are similar. Racially-matched students in the class who can view their instructor as a role model experience the most robust gains.[27]

The estimates of the control variables suggest that students who are significantly younger than the professor have less chance of passing the class but otherwise do not perform better or worse than others who are similar-aged or older. The student's age does not affect final grades independently either. Table 6 also shows that first-year students earn higher grades than other groups. Possibly, this is because they tend to be high achievers compared to other, more senior students in the same class. Alternatively, courses taken by these freshman students are easier. Sophomores and Juniors also tend to earn higher grades compared to Seniors.

[27] We broadened our Must-Take classes sample to include both required and non-required courses per the student's academic major, but offered by only one instructor, and re-estimated equation (1). That is, this sample includes all Must-Take and May-Take classes which were offered by only one instructor in a semester. This strategy adds to the power of our sample, though the drawback is a higher threat of student selection into their preferred instructor's classes since they may choose their electives strategically. Nevertheless, the results point to a significant (though smaller) race match effect for the youngest students in the class, and an offsetting effect for older race matched students, consistent with our main results.

The results in this section show that teacher-student racial congruence benefits accrue to only the younger students, underlining the importance of the role model effect as a critical channel for this effect.

3.2. Robustness Analyses

3.2.1. Alternative Definitions of Role Models

In our main specification, we defined the *Non-Role Model* variable as equal to one if the student is significantly older than the instructor or is "about the same age" as the instructor. In our baseline specification, equation (1), we used a ten-year threshold to construct the *Non-Role Model* variable. That is, this variable was equal to one if the instructor's age minus the student's age is ten or smaller. In Figures 3, 4, and 5, we present the results that pertain to alternative relative age thresholds for each outcome, *Completed the Class*, *Passed the Class*, and the *Final Grade*, respectively. In each of these figures, the solid and black line represents the coefficient of the *Race-Matched Instructor* in equation (1), and the dashed gray line signifies the sum of the coefficients of the *Race-Matched Instructor* and its interaction with the *Non-Role Model Instructor*. Each point shows a separate estimate of equation (1) with a different relative age threshold depicted on the horizontal axis. For example, the very first (leftmost) point on the solid line in Figure 5 is the estimate of β_1 from equation (1), where *the Non-Role Model Instructor* variable is constructed to take the value of one if the instructor is no more than *five* years older than the student (as opposed to *ten* in the baseline) or if the student is older than the professor. The figure shows that the estimated role model effect in this specification is 0.11, which is statistically significant at the 1% level. The very first point on the dashed line in the same graph is the sum of β_1 and β_2 using the same definition of the *Non-Role Model* variable. This estimate is -0.03, and it is not statistically significant at conventional levels. The results presented in Figures 3, 4, and 5 are similar to those given in Table 6, i.e., the baseline specification with ten years as the threshold (which are also depicted in the figures by the vertical dashed line). More specifically, these figures indicate that the benefits of a student-teacher race match are most potent for those younger students who can view their instructor as a role model, and coefficients on the interaction term are always negative, offsetting the main effect.[28]

Next, we investigate the differential effects of a race match using more precisely defined relative student age categories by estimating a slightly modified version of equation (1):

$$(5)\qquad Y_{ikstr} = \beta_1 Race\ Match_{ikst} + \sum_a \alpha_a Relative\ Age^a_{ikst} + \sum_a \theta_a Race\ Match_{ikst} \times Relative\ Age^a_{ikst} + \gamma X_{it} + \mu_i + \delta_{kst} + \theta_{kr} + \varepsilon_{ikstr},$$

where $Relative\ Age^a$ indicates the student's age category *a* relative to her/his instructor's age. For example, one of the relative age categories is *Student 10-15 Yrs. Younger Than Instructor*, which takes the value of one if the instructor's age minus the student's age is between 10 and 15. The other categories are *Student 5-10 Yrs. Younger Than Instructor*, *Student Within 5 Yrs. of Instructor*, *Student 5-10 Yrs. Older Than Instructor*, *Student 10-15 Yrs. Older Than Instructor*, and *Student More Than 15 Yrs. Older Than Instructor*. The omitted age category is made up of students who are more than 15 years younger than their professors. That is, the comparison group contains the youngest students, i.e., those for whom the role model effect is the most relevant.

Results obtained from equation (5) are displayed in Table 7. The estimates of *Race Matched Instructor* are positive and significant (and virtually identical to those in Table 6), suggesting that racial congruence with their instructor has large positive benefits for the youngest students. Most interaction terms between *Race Matched Instructor* and relative age categories, especially the ones that indicate that the student is around the same age as or older than her/his instructor, are negative. These results imply that benefits from student-teacher race matches accrue to significantly younger students. The most prominent differential effects of student-professor race matches are for students within five years of their instructor's age, suggesting that students closest to their instructor's age have the worst differential outcomes. This could be due to negative in-group bias on the part of the instructor. Instructors may have higher expectations for students that look like themselves, at least in terms of their race and age.

[28] Our results begin to change when we use thresholds greater than 11 years. This is expected, since many students for whom the role model effect is relevant are included in the *Non-Role Model* category when we allow for a very large age gap.

3.2.2. More Strict Definitions of a Must-Take Class

A threat to the identification of causal effects in our context is the possibility that students strategically time when they take a Must-Take class such that they are matched with a teacher of their preference. In our analysis in section 2.1.2 above, we show that about 40% of the students delay taking a Must-Take course, but those who delay taking the course and those who take it on time are equally likely to get teachers with favorable demographic characteristics, such as a same-race or role-model professor. In this section, using a more strict definition of a Must-Take class, we provide further evidence against the possibility that the strategic timing of course-taking drives our main results. Specifically, for this analysis, we use only the subset of Must-Take classes taught by the same instructors *two semesters in a row*. Said differently, our sample in this analysis includes only the observations from students' courses that their academic major requires without any alternatives and, at the same time, taught by the same instructor for at least two back-to-back semesters. Thus, the results from this sample will be less likely to be tainted by a bias due to strategic timing or delay by the student. The results of this analysis are given in Table 8. Despite the expected reduction in the number of observations, the pattern of the estimates is the same as those in our baseline specification in that the benefits from a race-matched professor accrue to the younger students but not to the old.

We repeated the same exercise with an even more strict definition of a Must-Take class in which we include only the required courses that the same instructor teaches for at least three consequent semesters. The results obtained from this analysis (Appendix Table 2) also show a pattern similar to those in our baseline specification (Table 6) and Table 8.

3.2.3. Strategic Academic Major Switching

When determining students' Must-Take classes in a semester, we used the courses designated as required for their academic major in that particular semester. Past research has demonstrated that besides earning low grades in the major's courses (Astorne-Figari and Speer, 2019), same-race instructors or role models may influence a student's tendency to switch academic majors (Porter and Serra, 2020; Kofoed and mcGovney, 2019). If a student's exposure (or lack of exposure) to same-race instructors causes a change in her/his major, our estimates may be biased. Another potential source of bias related to majors is that students strategically switch to other majors in the hopes of getting matched with instructors of their preference.

During our sample period, 42% of the students who took at least one Must-Take class switched majors.[29] To investigate whether these changes result from being exposed to race-matched instructors, we estimated our main specification, equation (1), with a different outcome that takes the value of one if the student changes to another major after taking the course. The point estimates from this regression of variables *Race-Matched Instructor*, *Non-Role Model Instructor*, and their interaction are all smaller than the standard errors of these estimates, indicating that contact with same-race instructors in a Must-Take class does not influence a student's propensity to switch majors in the future.

We further investigate whether our results are driven by students' "calculated" major changes by re-estimating our main model (equation 1) using the subset of students who never changed their majors. The results, presented in Table 9, are similar to those from the baseline specification (Table 6). As a final robustness check, we re-defined students' Must-Take classes using the course requirements of their major in their last semester instead of their concurrent majors. We again found that our estimates (shown in Appendix Table 3) were not sensitive to this modification. The evidence provided in this section suggests that our baseline results are not an artifact of strategic academic major selection by the students.

3.2.4. Familiarity with the Professor

Students who had a satisfactory experience with a professor may try to take another class with the same professor in the future. Because our estimates indicate that same-race professors improve students' grades, a professor may be more likely to be matched with a student of the same race in a future class than another dissimilar-raced student. To the extent that familiarity with a professor increases course outcomes, omitting this factor from the regressions may cause a bias in our estimates. Hwang, Kisida, and Coedel (2021) show that students who are familiar with their instructors tend to perform better in their classes at the elementary and middle school levels.

To address this issue, we included in the regressions a control variable that indicates whether the student had previously taken a course from their current instructor. Since this

[29] The majority (60%) of these switches were within the same college (e.g., an accounting major switching to a marketing major in the College of Business). This is expected because the majors in the same college are close to one another in substance and require similar courses, minimizing the risk of a delay in graduation.

measure varies within a student, we can add the variable *Previously Taken Instructor* to our set of controls in equation (1). In our sample, students have had previous experience with their instructor about a third of the time. Consistent with previous findings, the results shown in Appendix Table 4 demonstrate that students' course outcomes improve when they have previously taken a course from the instructor. More importantly, the coefficients of interest (β_1 and β_2) are virtually identical to our main results shown in Table 6 when we include this control variable, indicating that our race-match estimates are free from a bias that may arise from omitting students' familiarity with their professors.

3.3. Extensions

3.3.1. The Impact of Race Match on Midterm Grades

Professors at our university are asked to assign midterm grades to their students by the mid-semester.[30] The primary purpose of this practice is that midterm grades provide feedback to students about how well they perform early in the semester and help them make adjustments to improve. Although midterm grades are an imperfect measure of student performance and do not ultimately affect students' GPAs or progress toward graduation, they may still be essential performance indicators. For example, we found that midterm grades are very highly correlated with students' final grades and strongly predict whether the student withdraws from the class.[31] Instructors in about 85% of our Must-Take classes sample provided students with midterm grades.

We estimated equation (1) using the midterm grades as the outcomes to investigate whether the race-match effects start early in the semester. Results are reported in Table 10. In column 1, where the outcome variable indicates obtaining a passing midterm grade, we do not find any impact of teacher-student racial congruence. Column 2 shows that younger students with the same race as their instructor's race earn significantly higher midterm grades (0.095). In comparison, there is a large and significant negative differential effect for older students of the same race (-0.082). Consistent with the results above, the net impact of a race match for older

[30] Fall and Spring semesters last 14 weeks, and the midterm grades are due by the end of the 7th week.

[31] Specifically, obtaining a passing midterm grade reduces a student's chances of withdrawing from the class by 13 percentage points and increases the probability of passing the class by 36 percentage points.

students is not statistically different from zero (p-value 0.788). These results suggest that the benefits of an instructor-student race match start to be felt by students younger than their teachers early in the semester, while older students do not benefit.

3.3.2. The Impact of Student-Professor Race Match on Long-Term Outcomes

In this section, we investigate whether having a race-matched professor in a class has other impacts beyond that class by examining two additional outcomes. The first is whether the student will repeat a course in the future. In our sample, 4% of the time, students retook a course they had taken. Students typically repeat a course from which they obtained a low grade to improve their GPAs, as the university allows students to replace the low grade on their first attempt with the grade on their second attempt. In our estimation sample, failing a course or getting a low grade appears to be a strong predictor of whether the student will retake the course in the future.[32] This is not surprising because the Must-Take classes are designated as required by the student's program of study, and failing a required class will prevent them from obtaining the degree. Since our baseline estimates show that same-race instructors improve the student's grades, especially the younger ones, we expect that those who take a class from a same-race professor are less likely to repeat the course in the future. To investigate this possibility, we estimated equation (1) using an alternative outcome, *Repeat*, which takes the value of one if the student will retake the same course in the future and zero otherwise. Results obtained from this analysis are displayed in Table 11. The coefficient of the *Race-Matched Instructor* is -0.021, and that of its interaction with the *Non-Role Model Instructor* is 0.013. Both are statistically significant. These estimates indicate that young students whose races are the same as the instructor's race are less likely to repeat the same course in the future. However, consistent with our earlier results, this race-match effect does not apply to older students. Given that the university with which we are working charges approximately an extra $1,000 for each additional course, the estimates in Table 11 suggest that students who take classes from dissimilar-race professors may incur additional costs down the line.

[32] For example, 33% of those who failed the course or obtained a D repeat it in the future, while only 1% of those who got a A, B, or C did so.

Second, we investigate a more consequential long-term outcome: graduation, by estimating the equation depicted below:

(6) $Y_i = \gamma_1 \%RaceMatch \,\&\, RoleModel\ Inst_i + \gamma_2 \%RaceMatch \,\&\, NonRoleModel\ Inst_i + \delta X_i + \varepsilon_i$

where the unit of observation is a student. One of the two outcomes, *On-Time Graduation*, is an indicator that equals one if the student graduates from college within four years. We constructed this variable based on the observation of the student's first year and class standing in our sample and the semester in which she/he graduates. For example, if a student appears for the first time as a freshman in Fall 2012 semester in our sample and graduates by Spring 2016, then *On-Time Graduation* takes the value of one for this student. If we observe a student as a sophomore for the first time in Fall 2012, then the *On-Time Graduation* variable is equal to one only if the student graduates by Spring 2015. This is because a sophomore has already completed a year's worth of studies in the past, and to graduate from college on time, i.e., in four years, she/he must finish the rest of the coursework in three years. Note that in this regression, we only include the student who will be able to graduate within our sample period (2012-2017). For example, a student who begins her/his college career in Fall 2016 cannot be reasonably expected to graduate by the end of our sample period. Thus, such students are excluded from this analysis. The second outcome variable is the student's graduation GPA, conditional on graduating. That is, only students who graduated during our sample period enter this regression.

On the right-hand side of equation (6) are the two variables of interest that measure the shares of classes the students had taken from race-matched instructors. The $\%RaceMatch \,\&\, RoleModel\ Inst$ ($\%RaceMatch \,\&\, NonRoleModel\ Inst$) is the share of classes the student took from race-matched professors who are also role models (non-role models) as we defined earlier in the paper, i.e., the instructor is at least ten years older than the student (within ten years of age window of the student or younger than the student). The vector X includes the personal attributes of the student, such as her/his sex, race, age (at the time of the entry), and the number of semesters the student stayed in a dorm on campus. To compare students with the same college career trajectory, we also include in the regressions semester of entry-by-class standing at the entry-by-academic major fixed effects.

The point estimates and heterogeneity-robust White standard errors obtained from equation (6) are presented in Table 12. In column 1, where the outcome is *On-Time Graduation*, the coefficient of $\%RaceMatch$ & $RoleModel\ Inst$ is 0.365, indicating a ten percentage point increase in the student's share of race-matched and older professors increases student's probability of graduating on time from college by 3.65 percentage points.[33] On the other hand, the estimate of $\%RaceMatch$ & $NonRoleModel\ Inst$ is statistically not different from zero, suggesting that race-matched but younger professors do not help student's timely graduation. In column 2, where the outcome is the student's GPA at the time of graduation, both of the share variables are insignificant.

The findings in this section indicate that race-matched professors improve some of the long-term outcomes of the younger students who may view them as role models, while there are no long-term benefits for older students.

3.3.3. Heterogeneity by Majors' STEM Status

Students in our estimation sample are pursuing degrees in several (141) academic programs, some of which are considered in the Science, Technology, Engineering, and Mathematics (STEM) fields.[34] Past research investigated many issues surrounding STEM degrees, ranging from the underrepresentation of certain demographic groups in STEM majors (Sovero, Buchinsky, and Baird 2021, Bottia et al. 2015; Carrell, Page, and West 2010) to labor market returns to majoring in a STEM field (Webber 2014; Altonji, Blom, and Meghir 2012) and determinants of choosing a STEM degree in college (Delaney and Devereux 2021, Conger et al. 2021, Rask 2010, Kokkelenberg and Sinha 2010). In this section, we investigate whether the student-teacher race match effects are observed for students in STEM majors versus those in other programs.

For the purposes of our paper, it is important to highlight two critical qualities that differentiate STEM students from others. First, STEM students are typically of higher quality, overachieving, and highly motivated. For example, past research has shown that students who

[33] Students complete approximately 40 courses to obtain a degree. Thus a 10% increase corresponds to 4 additional courses. The average of *On-Time Graduation* is 0.37, meaning nearly 40% of students graduated in four years.

[34] We reviewed and classified the STEM status of the major names listed in our transcript data according to the Department of Homeland Security's STEM Designated Degree Program List.

will have chosen a STEM major in college are successful in middle and high school, securing higher grades in their science and math classes, obtaining high standardized test scores, and completing multiple advanced placement courses. Second, the evaluation of students' performance in STEM program courses is less vulnerable to teachers' biases compared to courses in non-STEM programs. For example, a math student may be asked to evaluate a definite integral in a test. In this case, the student's performance is judged by whether she/he could correctly perform the integration and obtain the correct numerical answer. On the contrary, a student in a non-STEM major, such as humanities, may be asked to write an essay on a topic. Because there is no single correct answer but many possibly valid answers to such an assignment, the teacher's subjective opinions may influence the student's grade.[35]

To investigate whether student-teacher race match effects apply to students in STEM fields versus others, we estimate equation (1) over these samples separately. The results are presented in Table 13. Columns 1-2 pertain to the STEM majors sample. The coefficients of *Race Match* in these regressions are small and statistically insignificant. The interactions of *Race Match* and *Non-Role-Model Instructor* are negative but statistically not different from zero in column 2. The estimates obtained from non-STEM students (in columns 3 and 4 of Table 13) are strikingly different. In these regressions, the estimates of *Race Match* are large and positive, and the coefficients of *Race-Matched* × *Non-Role-Model Instructor* are negative. All of them are statistically significant.

The estimates in Table 13 suggest that student-teacher race-match effects apply to neither young nor old STEM students' course grades, while the young students in non-STEM programs, but not their older classmates, benefit from taking a class from a race-matched professor. This stark contrast could be explained by the differences between STEM versus non-STEM majors we mentioned above. Specifically, due to the more objective nature of STEM courses/exams relative to the non-STEM courses, non-STEM students' grades are less likely to be impacted by

[35] In addition, STEM and non-STEM majors may differ in terms of their occupational specificity (Becker 1962). Students in more "specific" ("general") majors acquire skills that are applicable only to a handful (a large number) of jobs. Thus, graduates of "specific" ("general") majors are (not) clustered in a few occupations. Using the American Community Surveys (ACS) of 2012-2018, we computed a Herfindahl-Hirschman Index (HHI) value for each major by first calculating the share of every major's graduates in each occupation and then adding up the squares of these shares. Majors with a high HHI value are more "specific" in that individuals with such college majors are most frequently seen in a few jobs. The median STEM major's HHI was 0.034, while it was 0.020 for non-STEM majors. However, a more detailed look at the distribution of HHI's revealed that both STEM and non-STEM groups included high- and low-HHI majors. Consistent with Leighton and Speer (2020), it can be concluded that STEM majors tend to be, though are not necessarily, more specific than non-STEM majors.

the professor's bias. In addition, the Role Model channel (increasing students' motivation in their field of study and coaching them about labor market opportunities) may not be applicable to STEM students as students in STEM majors are already highly motivated.

3.3.4. Heterogeneity by Instructor Value-Added

As a final extension analysis, we examine the heterogeneity of the student-professor race-match effects and the role model channel by professor quality. No doubt, the quality of an instructor is hard to measure comprehensively, and instead, we rely on teacher value-added measures as a proxy. Specifically, we construct professors' value-added to the course grades of their students using the methodology described in Chetty, Friedman, and Rockoff (2014a and 2014b). They suggest that conditional on past academic achievement, their value-added estimates predict teachers' impact on test scores, and high value-added teachers improve students' long-term educational and labor market outcomes.[36] We do not have access to the data on students' past academic achievement. Instead, we exploit the repeated student observations in our transcript data. That is, we construct the value-added estimates conditional on student fixed effects (in addition to those described in Chetty, Friedman, and Rockoff, 2014a). The distribution of the value-added estimates for the instructors in the Must Take classes sample is depicted in Figure 6. By construction, the distribution is centered around zero. Those with positive (negative) value-added estimates are above (below) the average within the university. The variation in our value-added estimates is smaller for our college instructor sample than the traditional estimates obtained for the high-school teachers. This is because the variation in a college student's course grades (A=4, B=3, C=2, D=1, and F=0) is much smaller than the standardized test scores.

By definition, students of high value-adding, high-quality instructors earn better course grades on average. However, we do not know whether high-quality instructors achieve this by improving the grades of *some* students, e.g., students of a particular race or age, versus grades of *all* students regardless of their race or age. In other words, under one hypothesis, we should

[36] Despite criticism, e.g., Rothstein (2017), this method has been widely used by a number of researchers to estimate K-12 teachers' value-added to their students' standardized test scores (Hanushek and Rivkin 2010). Value-added estimates have also been used to inform personnel decisions and improve workforce quality. Koedel, Mihaly, and Rockoff (2015) provide an overview of this literature.

observe more considerable race-match effects for the students whose professors have a higher value-added. For example, it is plausible that a White professor motivates her/his White students exceptionally well but not Black students, and these White students earn high course grades. Since White students make up the majority of most classes, we would observe a sizeable race-match effect for high-value-adding professors. On the contrary, under the alternative hypothesis, high-quality instructors can effectively motivate students of all races and ages equally. If this is the case, we should not observe a race-match or role-model effect for the professors whose value-added is high.

To test this conjecture, we first categorized instructors into three groups according to their estimated value-added. Low- and high-value-adding instructors are those whose value-added estimate is in the distribution's bottom and top 25 percentile, respectively. Those within the 25th and the 75th percentiles are categorized as medium-value-adding professors. We then estimate equation (1) over these subsamples separately. The results are presented in Table 14, where, for brevity, we only show the results obtained for the out *Final Grade* outcome. Columns 1, 2, and 3 pertain to the results from the low-, medium-, and high-value-added professors, respectively. In columns 1 and 2, the coefficients of the *Race-Matched Instructor* variable are positive and significant, and those of the interactions are negative. This finding implies that low- and medium-quality professors improve the grades of younger students of the same race relative to students of different races, and this race-match effect does not apply to older students. Strikingly, the relationship is entirely different for the high-value-adding instructors in column 3. There is no race-match or role-model effect to speak of for these high-caliber professors.[37] These results suggest that high-value-adding teachers may be attaining this status by motivating all students rather than focusing on only one group.

4. Summary and Conclusion

An extensive amount of research has documented that educational outcomes of students of a particular race improve if their teachers are also of the same race as them. Besides teachers' biases in favor of/against certain racial groups, other explanations for this finding include the Role Model effect. According to this channel, a student from a certain racial background is not

[37] We also experimented with dividing teachers by the median value-added. The results, available upon requests, were similar to those in Table 14.

fully aware of potential career trajectories she/he can pursue with his degree. The teacher, who is also of the same race as the student, informs the student of these options and provides her/him with guidance thanks to the expertise and knowledge of potential hardships that individuals with their racial background may face. As a result, the student updates her/his beliefs on the return to studying in this field and becomes more motivated, ultimately improving academic achievement.

In this paper, we propose that the Role Model mechanism can be relevant only or primarily for students who are younger than the teacher. This is because an older and, thus, a more experienced teacher can better predict the potential future challenges her student may face and guide the student past them. In contrast, a young teacher may not be aware of the hardships that the older student can come up against at a stage in life that the young professor has not experienced yet. Under this hypothesis, we expect student-teacher race racial congruence to have a more significant impact on younger students' educational outcomes than on older students. Note that past papers could not test this hypothesis because either it was not possible (for example, in K-12 settings) or their sample did not include enough older students (for example, most college students are younger than their professors).

Using data obtained from a Carnegie R1-designated university, where a significant share of the student body is composed of students older than traditional college age, we test whether student-teacher race matches impact students' course grades and, importantly, whether this effect varies by student's age relative to the teacher. To guard against biases that may arise due to the non-random sorting of students into classes/instructors, we use a restricted sample of classes required by the student's major and taught by only one professor. In these classes, the student cannot pick and choose her/his preferred instructor. In accord with the findings in the literature, our results show that students who are significantly younger than their professors and whose races are the same as their professors obtain higher grades in their classes. For example, when matched with a professor of the same race, young students are 2% more likely to receive a passing grade, and their final grade increases by 0.1-0.2 (out of a 4.0 scale). In contrast to the young college students, their classmates who are similar in age to or older than their professor do not benefit from a same-race professor at all. We show that the most adversely impacted age group comprises students who are within five years of their instructor's age. In a series of robustness analyses, we show that our results are not contaminated by biases that may arise due to the strategic course-taking behavior of students. Specifically, we provide evidence that calculated registration for easy courses or preferred instructors, postponing to take required courses, and planned academic major switching does not drive our estimates. Our findings suggest that the Role Model effect could be one of the main channels through which student-teacher race matches affect student achievement.

The race-match effect for the younger students starts early in the semester, influencing a student's midterm grades around the middle of the semester. Moreover, these effects persist in the long term. For example, young, but not old, students are less likely to repeat a course in the future if she/he has the same race as the professor. In addition, more courses taken from older and same-race professors increase the probability that a student will graduate on time, i.e., in four years. However, courses taken from younger same-race professors do not affect timely graduation. We show that the race-match effects are driven by students who pursue degrees in non-STEM fields, such as art, humanities, and business, and we find a null impact for STEM students. This finding could be because of differences in student quality and motivation and the evaluation methods in the non-STEM fields compared to the STEM fields. Finally, we find that the race-match effects are present only in classes taught by lower-quality professors (those with a low value-added to student grades). Remarkably different, in classes taught by the highest-caliber professors, there is no racial congruence effect for either the young or the old students. This finding suggests that the best instructors may be inspiring all students regardless of their race or age.

An oversimplified and unjustified conclusion from our analysis would suggest that education could be more effective if students and teachers were segregated along racial lines. This determination is wrong for many reasons, but especially because of the numerous benefits that arise when students are exposed to diversity during their time in school. For example, researchers have found that White students who engage with Black peers early in their college careers are more likely to select a Black roommate in the future (Carrell, Hoekstra, and West 2019), have significantly more Black friends in the future (Camargo, Stinebrickner, and Stinebrickner 2010), and tend to be more empathetic and more supportive of affirmative action (Boisjoly et al. 2006). Additionally, Lau (2022) provides direct evidence of the academic performance benefits caused by exposure to diversity in a class. Indeed, any identified benefits due to racial uniformity are minuscule compared to the benefits of diverse classrooms.

It is also naïve to conclude from our analysis that universities should recruit only old professors. Though these senior professors may be more likely to be viewed as role models by their students, past research has shown that there are benefits to hiring young professors. For example, a recent study by Packalen and Bhattacharya (2019) shows that younger researchers are more likely to use and build on new ideas. In an investigation of the effects of aging on scientific productivity, Gingras et al. (2008) find that researchers of all ages play important roles.

Instead, the implications of our analysis are as follows. As Dee (2004) emphasized, there is a gap in our understanding of the exact mechanisms by which same-race teachers influence student achievement. We provide evidence that the Role Model Effect could be one of the primary channels through which student outcomes are improved due to student-teacher racial congruence. This points to the need for high-quality educators to direct and inspire *all* students in their pursuit of education and career-oriented goals. In fact, some of our results imply that the highest quality professors motivate and improve students with any demographic attribute, not just one race or age group. Past papers have identified evidence for the importance of strong role models and the way they can influence a student's decisions. For example, Dasan (2019) and Lindholm (2004) discuss the importance of professorial and academic role models in shaping the career aspirations of future academics. Researchers have also documented the important influence of role models in many other contexts, such as in the field of economics (Porter and Serra 2020). Our results highlight the need for improved training of educators. Ideally, future researchers will find no disparities between the learning outcomes of students who match their teachers' race and those who do not. This will be the case when educators can motivate, guide, and instruct all students equally.

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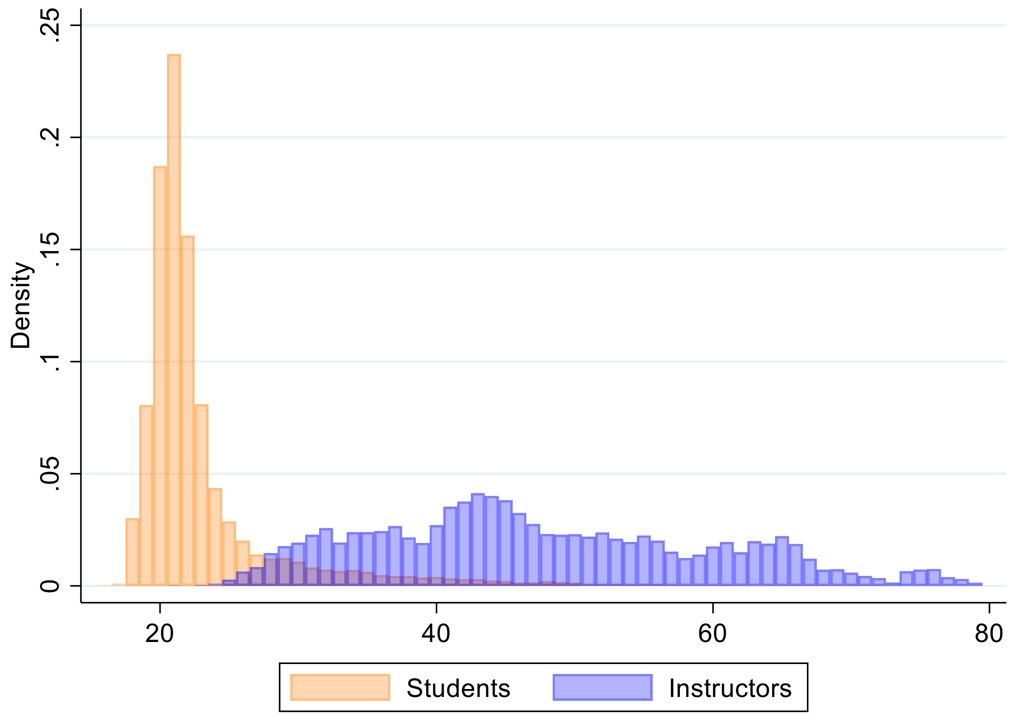
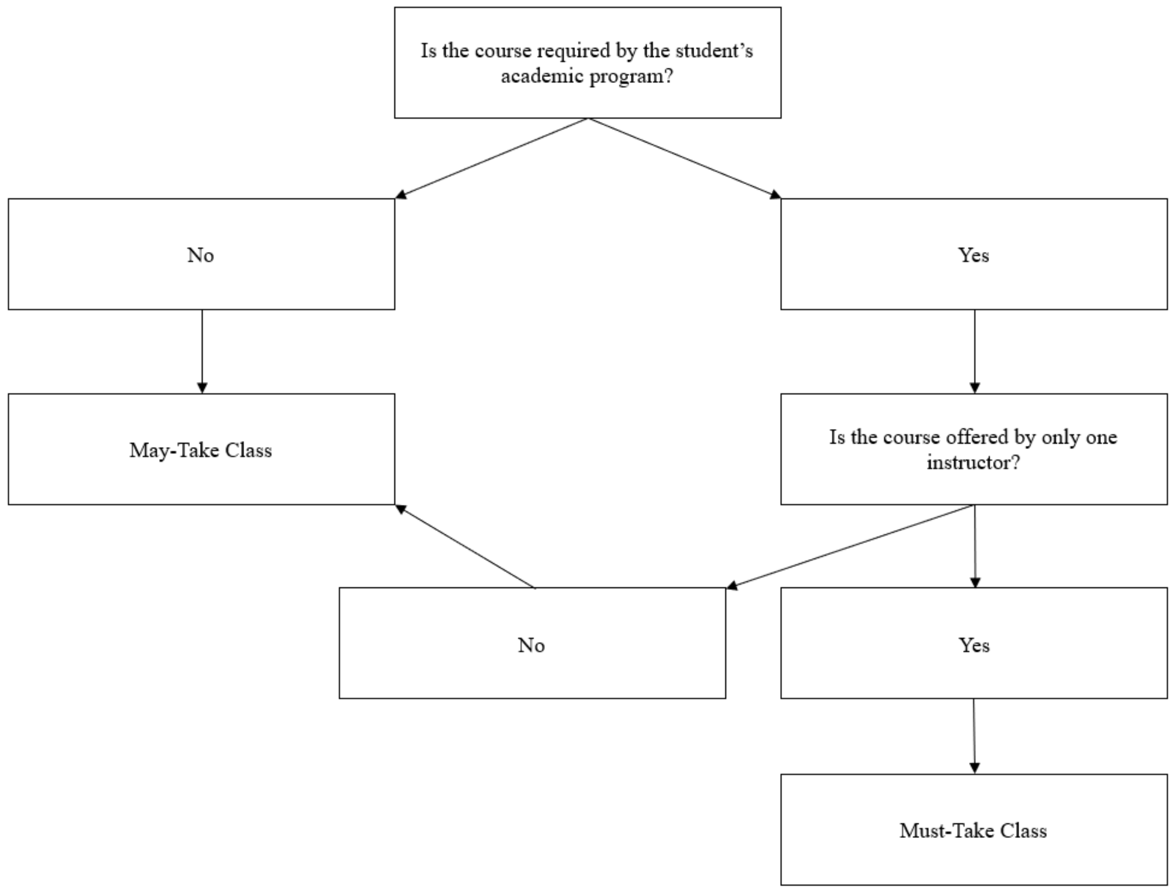
Figure 1
Student and Instructor Age Distributions



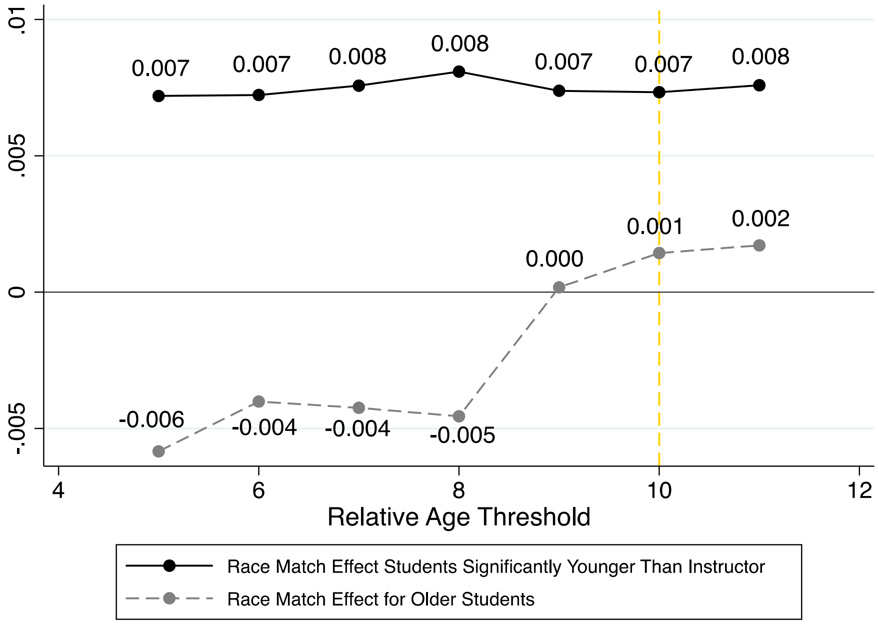
The distribution of student and instructor ages in the Must-Take classes sample.

Figure 2
Identifying Must-Take Classes



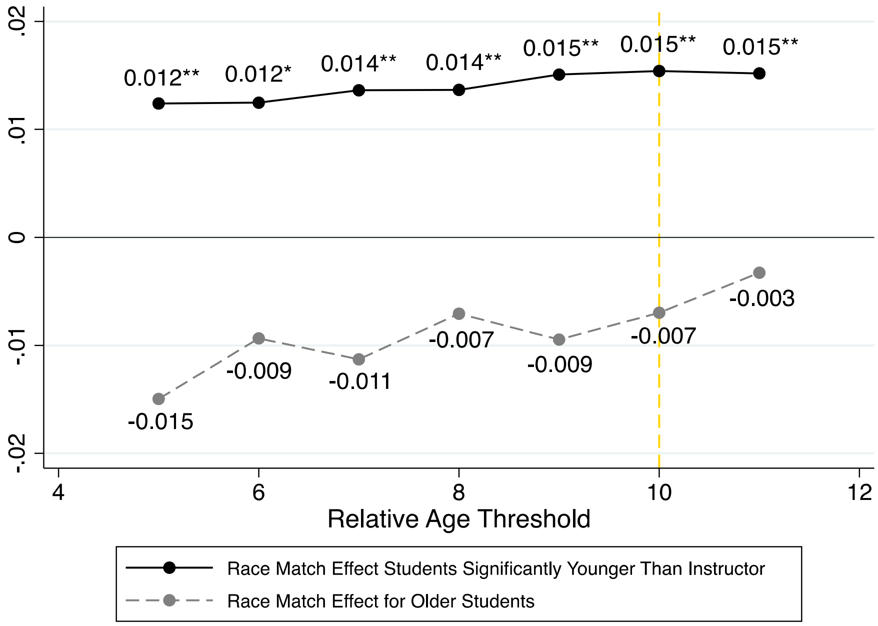
Flowchart for the decision rules determining whether a class is Must-Take or May-Take. The total number of classes is 38,258. Sixteen percent of all classes are classified as Must-Take for at least one student, while the remaining are classified as May-Take.

Figure 3
Estimates with Alternative Definitions of Role Models (5- to 11-Year Thresholds)
Outcome: Completed the Class



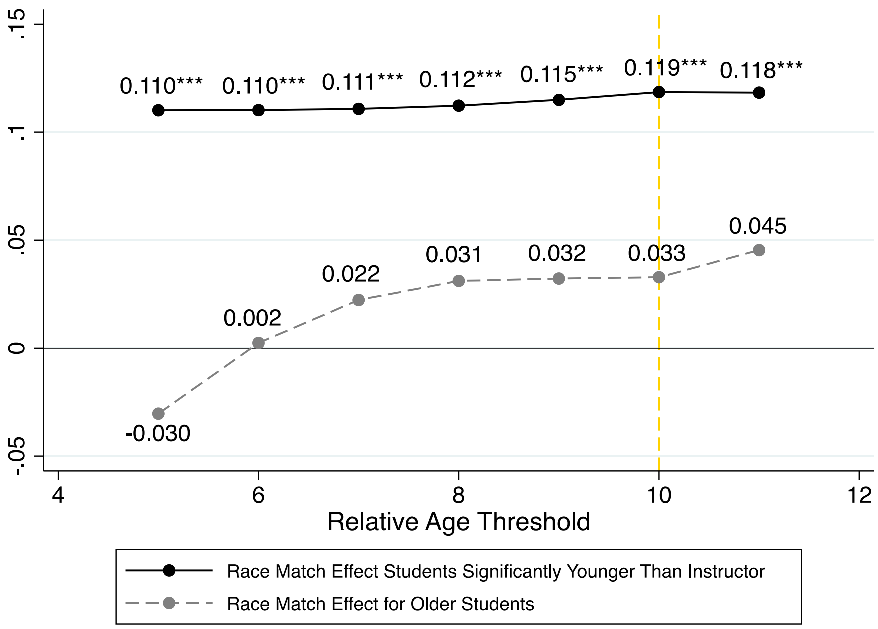
Estimates are obtained from equation (1). Only students in must-take classes are included in the regressions. The solid black line represents coefficients on Race-Matched Instructor (β_1). The dashed gray line represents the sum of Race-Matched Instructor (β_1) and Race-Matched × Non-Role-Model Instructor (β_2). Each pair of coefficients represents a separate regression. The horizontal axis denotes the relative age threshold used to calculate Non-Role-Model Instructor. The yellow vertical dashes highlight baseline estimates. The outcome is an indicator equal to one if the student completed the class. Standard errors are clustered at the class level. *, **, and *** indicate the impact is statistically significant at the 10%, 5%, and 1% levels.

Figure 4
Estimates with Alternative Definitions of Role Models (5- to 11-Year Thresholds)
Outcome: Passed The Class



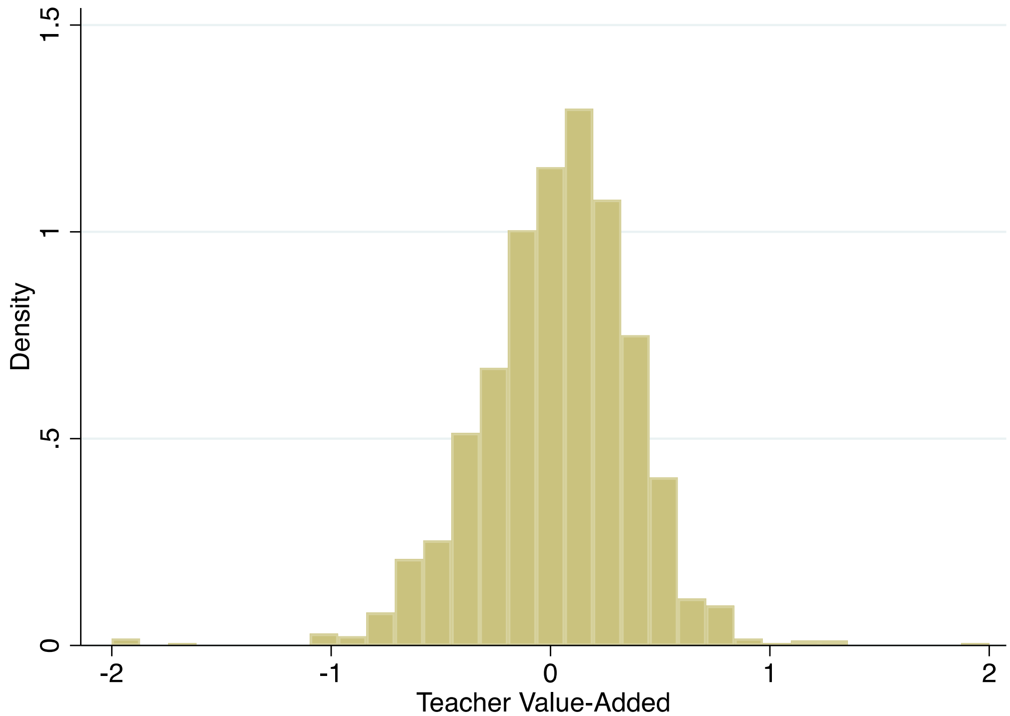
See notes in Figure 3. The outcome is an indicator equal to one if the student did not fail the class.

Figure 5
Estimates with Alternative Definition of Role Models (5- to 11-Year Thresholds)
Outcome: Final Grade



See notes in Figure 3. The outcome is the student's final grade, measured on a 4.0 scale.

Figure 6
Distribution of Instructor Value-Added Estimates



The distribution of instructor value-added for instructors in the Must-Take classes sample.

Table 1
Test for Student Selection Based on Instructor Characteristics in *May-Take Classes*

Panel A:

	(1)	(2)	(3)	(4)
	Black Instructor	White Instructor	Asian Instructor	Hispanic Instructor
%Black Students in the Class	0.093***			
	(0.011)			
%White Students in the Class		0.085***		
		(0.013)		
%Asian Students in the Class			0.139***	
			(0.053)	
%Hispanic Students in the Class				0.013
				(0.019)
Constant	0.025***	0.784***	0.055***	0.037***
	(0.003)	(0.009)	(0.001)	(0.001)
N	25,146	25,146	25,146	25,146
Course×Term FEs	Yes	Yes	Yes	Yes

Panel B:

	(1)	(2)	(3)	(4)
	In Past Classes, Average Grades Assigned by the Instructor to …			
	Black Students	White Students	Asian Students	Hispanic Students
%Black Students in the Class	0.011			
	(0.018)			
%White Students in the Class		0.041***		
		(0.012)		
%Asian Students in the Class			0.221***	
			(0.067)	
%Hispanic Students in the Class				0.027
				(0.041)
Constant	2.670***	3.143***	3.184***	3.041***
	(0.006)	(0.008)	(0.004)	(0.003)
N	23,041	23,251	20,091	22,077
Course×Term FEs	Yes	Yes	Yes	Yes

Table 1 Continued

Panel C:

	(1)	(2)	(3)	(4)
	Instructor's Age …			
	Under 30	30 to 40	40 to 50	Over 50
%Students 20 to 30 in the class	-0.132***	-0.011	0.046**	0.097***
	(0.014)	(0.020)	(0.020)	(0.020)
%Students 30 to 40 in the class	-0.184***	-0.081***	0.104***	0.161***
	(0.018)	(0.028)	(0.030)	(0.030)
%Students 40 to 50 in the class	-0.216***	-0.036	0.137***	0.116***
	(0.023)	(0.044)	(0.045)	(0.045)
%Students Over 50 in the Class	-0.177***	-0.057	0.226***	0.008
	(0.047)	(0.072)	(0.075)	(0.075)
Constant	0.215***	0.292***	0.219***	0.275***
	(0.011)	(0.015)	(0.015)	(0.015)
N	25,146	25,146	25,146	25,146
Course×Term FEs	Yes	Yes	Yes	Yes

Estimates are obtained from equation (2). The unit of observation is a class. Only students in may-take classes are included in the regressions. In Panel C, the omitted category comprises students under 20 years old. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 2
Summary Statistics of *Must-Take Classes*

Variable	Description	Full Sample	Students Whose Races Are the Same as the Instructor's Race	Students Whose Races Are Different from the Instructor's Race
Outcomes				
Completed the Class	=1 if the student did not withdraw from the class	0.97	0.97	0.97
Passed the Class	=1 if the student did not fail the class	0.95	0.96	0.93
Final Grade	The student's final grade for the class, measured on a 4.0 scale	3.05	3.20	2.82
Midterm Grade	The student's midterm grade for the class, measured on a 4.0 scale	2.94	3.09	2.73
Variables of Interest				
Race-Matched Instructor	=1 if the instructor and student are the same race	0.60	1.00	0.00
Non-Role-Model Instructor	=1 if the student's age is within 10 years of, or greater than, the age of the instructor	0.15	0.14	0.17
Instructor Attributes				
Instructor's Age	The instructor's age in years	47.51	48.46	46.07
Female Instructor	=1 if the instructor is female	0.50	0.52	0.47
White Instructor	=1 if the instructor is White	0.86	0.98	0.67
Asian Instructor	=1 if the instructor is Asian	0.09	0.00	0.22
Black Instructor	=1 if the instructor is Black	0.03	0.01	0.05
Hispanic Instructor	=1 if the instructor is Hispanic	0.02	0.00	0.06
Other Race Instructor	=1 if the instructor is not White, Black, Asian, or Hispanic	0.00	0.00	0.01

Table 2 Continued				
Variable	**Description**	**Full Sample**	**Students Whose Races Are the Same as the Instructor's Race**	**Students Whose Races Are Different from the Instructor's Race**
Student Characteristics				
Student Age	The student's age in years	23.11	23.12	23.09
Lives in Dorm	=1 if the student lives in a dormitory.	0.20	0.18	0.24
Female Student	=1 if the student is female	0.62	0.62	0.62
White Student	=1 if the student is White	0.69	0.98	0.24
Asian Student	=1 if the student is Asian	0.01	0.00	0.03
Black Student	=1 if the student is Black	0.25	0.01	0.61
Hispanic Student	=1 if the student is Hispanic	0.03	0.00	0.07
Other Race Student	=1 if the student is not White, Black, Asian, or Hispanic	0.02	0.00	0.05
Freshman	=1 if the student is a freshman	0.05	0.05	0.06
Sophomore	=1 if the student is a sophomore	0.12	0.12	0.12
Junior	=1 if the student is a junior	0.27	0.28	0.27
Senior	=1 if the student is a senior	0.55	0.56	0.55
N		68,643	41,370	27,273

The unit of observation is a student-class. Only students in must-take classes are included. Summary statistics for Completed Class (row 1) are from the sample, including observations for students who did not complete the class (N=74,681). Statistics for Midterm Numeric Grade (row 4) are from the sample of students who received a midterm grade for the class (N=57,147). All other statistics pertain to students who complete the class.

Table 3
Course Timing Relationship with Race-Matched and Non-Role-Model Instructors in *Must-Take Classes*

	(1)	(2)
	On-Time Course Taking	Delayed Course Taking
Race-Matched Instructor	-0.001	0.003
	(0.011)	(0.008)
Race-Matched x Non-Role-Model Instructor	-0.010	0.002
	(0.013)	(0.009)
Non-Role-Model Instructor	-0.005	0.001
	(0.013)	(0.009)
N	68,643	68,643
Controls	Yes	Yes
Student FEs	Yes	Yes
Class FEs	Yes	Yes
Course x Race FEs	Yes	Yes

Estimates are obtained from equation (1). The unit of observation is a student-class. Only students in must-take classes are included in the regressions. Race Matched Instructor is an indicator equal to one if the student and instructor have the same race. Non-Role-Model Instructor is an indicator equal to one if the student's age is within ten years of, or greater than, their instructor's age. The outcome in column 1 is an indicator that equals one if the student takes the course during the recommended year by the university bulletin. The outcome in column 2 is an indicator equal to one if the student takes the course after the recommended year. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4
Test for Student Selection Based on Instructor Characteristics in *Must-Take Classes*

Panel A:

	(1)	(2)	(3)	(4)
	Black Instructor	White Instructor	Asian Instructor	Hispanic Instructor
%Black Students in the Class	0.005			
	(0.009)			
%White Students in the Class		0.029		
		(0.018)		
%Asian Students in the Class			0.030	
			(0.072)	
%Hispanic Students in the Class				-0.001
				(0.012)
Constant	0.026***	0.817***	0.103***	0.031***
	(0.003)	(0.013)	(0.003)	(0.001)
N	5,862	5,862	5,862	5,862
Course & Term FEs	Yes	Yes	Yes	Yes

Panel B:

	(1)	(2)	(3)	(4)
	In Past Classes, Average Grades Assigned by the Instructor to …			
	Black Students	White Students	Asian Students	Hispanic Students
%Black Students in the Class	0.006			
	(0.026)			
%White Students in the Class		0.000		
		(0.016)		
%Asian Students in the Class			-0.009	
			(0.093)	
%Hispanic Students in the Class				0.082
				(0.063)
Constant	2.684***	3.228***	3.220***	3.075***
	(0.008)	(0.011)	(0.005)	(0.005)
N	5,577	5,611	5,120	5,421
Course & Term FEs	Yes	Yes	Yes	Yes

Table 4 Continued

Panel C:

	(1)	(2)	(3)	(4)
	Instructor's Age …			
	Under 30	30 to 40	40 to 50	Over 50
%Students 20 to 30 in the Class	0.037	-0.055	0.017	0.001
	(0.030)	(0.041)	(0.040)	(0.041)
%Students 30 to 40 in the Class	0.056	0.008	0.024	-0.088
	(0.038)	(0.059)	(0.058)	(0.059)
%Students 40 to 50 in the Class	0.049	0.051	0.020	-0.120
	(0.041)	(0.076)	(0.075)	(0.082)
%Students Over 50 in the Class	0.012	0.074	0.084	-0.170
	(0.063)	(0.114)	(0.109)	(0.125)
Constant	0.023	0.261***	0.308***	0.408***
	(0.027)	(0.037)	(0.036)	(0.037)
N	5,862	5,862	5,862	5,862
Course & Term FEs	Yes	Yes	Yes	Yes

Estimates are obtained from equation (3). The unit of observation is a class. Only students in Must-Take classes are included in the regressions. In Panel C, the omitted category comprises students under 20 years old. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 5
Test for Student Sorting in *Must-Take Classes* Based on Past Achievement

	In Semester t, %Classes Taken from …			
	…Race-Matched Instructors		…Non-Role-Model Instructors	
	(1)	(2)	(3)	(4)
Cumulative GPA at the Start of Semester t	0.005	0.007	-0.003	-0.003
	(0.009)	(0.009)	(0.010)	(0.010)
N	31,639	31,639	31,639	31,639
Controls	No	Yes	No	Yes
Student & Term FEs	Yes	Yes	Yes	Yes

Estimates are obtained from equation (4). The unit of observation is a student-term. The outcome in columns 1 and 2 is the share of same-race instructors that the student has each term. The outcome in columns 3 and 4 is the share of similarly-aged or younger instructors the student has each term. Cumulative Past GPA is the student's cumulative weighted GPA in classes taken at the University as of the beginning of the semester. Only students in must-take classes are included in the regressions. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 6
Differential Effects of a Race Match by Relative Student Age in *Must-Take Classes*

	(1)	(2)	(3)
	Completed the Class	Passed the Class	Final Grade
Race-Matched Instructor	0.007	0.015**	0.119***
	(0.005)	(0.007)	(0.027)
Race-Matched × Non-Role-Model Instructor	-0.006	-0.022***	-0.086***
	(0.006)	(0.007)	(0.029)
Non-Role-Model Instructor	0.002	0.013**	0.031
	(0.006)	(0.007)	(0.026)
Student’s Age	0.004*	-0.003	-0.015
	(0.002)	(0.003)	(0.012)
Lives in Dorm	-0.003	0.008**	0.019
	(0.003)	(0.004)	(0.016)
Freshman	0.006	0.031***	0.127***
	(0.007)	(0.010)	(0.038)
Sophomore	0.001	0.015***	0.040*
	(0.004)	(0.005)	(0.021)
Junior	0.001	0.008***	0.044***
	(0.002)	(0.003)	(0.012)
Constant	0.868***	1.010***	3.306***
	(0.054)	(0.069)	(0.288)
N	74,681	68,643	68,643
$\beta_1 + \beta_2 = 0$ test P-value	0.828	0.370	0.325
Student FEs	Yes	Yes	Yes
Class FEs	Yes	Yes	Yes
Course x Race FEs	Yes	Yes	Yes

Estimates are obtained from equation (1). The unit of observation is a student-class. Only students in Must-Take classes are included in the regressions. Race-Matched Instructor is an indicator equal to one if the student and instructor have the same race. Non-Role-Model Instructor is an indicator equal to one if the student’s age is within ten years of, or greater than, their instructor’s age. The outcome in column 1 is an indicator equal to one if the student completed the class. The outcome in column 2 is an indicator equal to one if the student did not fail the class. The outcome in column 3 is an indicator equal to one if the student received an A in the class. The outcome in column 4 is the student’s final grade, measured on a 4.0 scale. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 7
Differential Effects of a Race Match by Relative Student Age Using Five-Year Age Groups in *Must-Take Classes*

	(1)	(2)
	Passed the Class	Final Grade
Race-Matched Instructor	0.016**	0.117***
	(0.007)	(0.029)
Race-Matched Instructor × …		
… Student 10-15 Yrs. Younger Than Inst.	-0.001	0.004
	(0.008)	(0.030)
… Student 5-10 Yrs. Younger Than Inst.	-0.017**	-0.046
	(0.009)	(0.035)
… Student Within 5 Yrs. of Inst.	-0.034***	-0.165***
	(0.011)	(0.044)
… Student 5-10 Yrs. Older Than Inst.	-0.029	-0.107
	(0.020)	(0.095)
… Student 10-15 Yrs. Older Than Inst.	-0.038	-0.139
	(0.027)	(0.117)
… Student More Than 15 Yrs. Older Than Inst.	-0.055**	-0.106
	(0.026)	(0.128)
Student 10-15 Yrs. Younger Than Inst.	-0.002	-0.006
	(0.007)	(0.028)
Student 5-10 Yrs. Younger Than Inst.	0.008	0.001
	(0.008)	(0.033)
Student Within 5 Yrs. of Inst.	0.010	0.058
	(0.011)	(0.044)
Student 5-10 Yrs. Older Than Inst.	0.017	-0.004
	(0.018)	(0.083)
Student 10-15 Yrs. Older Than Inst.	-0.011	-0.109
	(0.022)	(0.102)
Student More Than 15 Yrs. Older Than Inst.	-0.006	-0.143
	(0.028)	(0.132)
N	68,643	68,643
Controls	Yes	Yes
Student FEs	Yes	Yes
Class FEs	Yes	Yes
Course x Race FEs	Yes	Yes

Estimates are obtained from equation (5). The unit of observation is a student-class. Only students in must-take classes are included in the regressions. Race-Matched Instructor is an indicator equal to one if the student and instructor have the same race. Grade outcomes are the same as those shown in Table 4. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 8
Differential Effects of a Race Match by Relative Student Age
Using the Sample of *Must-Take Classes* Taught by the Same Instructor in At Least Two Consecutive Semesters

	(1)	(2)	(3)
	Completed the Class	Passed the Class	Final Grade
Race-Matched Instructor	0.010	0.043**	0.243***
	(0.008)	(0.017)	(0.065)
Race-Matched × Non-Role-Model Instructor	0.000	-0.037**	-0.194***
	(0.011)	(0.015)	(0.064)
Non-Role-Model Instructor	0.003	0.023*	0.089*
	(0.011)	(0.013)	(0.050)
Student's Age	0.006	-0.001	-0.033
	(0.004)	(0.006)	(0.023)
Lives in Dorm	-0.004	0.007	0.051*
	(0.005)	(0.007)	(0.030)
Freshman	0.000	0.041**	0.111*
	(0.011)	(0.018)	(0.067)
Sophomore	0.001	0.017*	0.019
	(0.007)	(0.009)	(0.039)
Junior	0.001	0.014**	0.044*
	(0.004)	(0.006)	(0.023)
Constant	0.831***	0.930***	3.622***
	(0.100)	(0.127)	(0.514)
N	28,121	24,137	24,137
$\beta_1 + \beta_2 = 0$ test P-value	0.423	0.773	0.547
Student FEs	Yes	Yes	Yes
Class FEs	Yes	Yes	Yes
Course x Race FEs	Yes	Yes	Yes

Estimates are obtained from equation (1). The unit of observation is a student-class. Only students in Must-Take classes led by instructors who offered the course in at least two consecutive semesters are included in the regressions. Race-Matched Instructor is an indicator equal to one if the student and instructor have the same race. Non-Role-Model Instructor is an indicator equal to one if the student's age is within ten years of, or greater than, their instructor's age. Outcomes are the same as those shown in Table 4. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 9
Differential Effects of a Race Match by Relative Student Age Using the Sample of Students that Never Switched Majors in *Must-Take Classes*

	(1)	(2)	(3)
	Completed the Class	Passed the Class	Final Grade
Race-Matched Instructor	0.009	0.020**	0.062*
	(0.006)	(0.009)	(0.037)
Race-Matched × Non-Role-Model Instructor	-0.010	-0.035***	-0.144***
	(0.008)	(0.009)	(0.038)
Non-Role-Model Instructor	0.003	0.019**	0.052
	(0.007)	(0.009)	(0.036)
Student's Age	0.010***	-0.004	-0.010
	(0.003)	(0.004)	(0.017)
Lives in Dorm	0.001	-0.002	0.016
	(0.004)	(0.005)	(0.021)
Freshman	-0.007	0.019	0.125**
	(0.010)	(0.013)	(0.052)
Sophomore	-0.012**	0.022***	0.043
	(0.005)	(0.007)	(0.028)
Junior	-0.005	0.011***	0.050***
	(0.003)	(0.004)	(0.016)
Constant	0.734***	1.017***	3.259***
	(0.068)	(0.090)	(0.390)
N	43,001	39,613	39,613
$\beta_1 + \beta_2 = 0$ test P-value	0.840	0.167	0.076
Student FEs	Yes	Yes	Yes
Class FEs	Yes	Yes	Yes
Course x Race FEs	Yes	Yes	Yes

Estimates obtained from equation (1). The unit of observation is a student-class. Students in must-take classes that never switched their major are included in the regressions. Race-Matched Instructor is an indicator equal to one if the student and instructor have the same race. Non-Role-Model Instructor is an indicator equal to one if the student's age is within 10 years of, or greater than, their instructor's age. Grade outcomes are the same as those shown in Table 6. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 10
Differential Effects of a Race Match by Relative Student Age – Midterm Grades in *Must-Take Classes*

	(1)	(2)
	Midterm Pass	Midterm Grade
Race-Matched Instructor	0.009	0.095**
	(0.010)	(0.041)
Race-Matched × Non-Role-Model Instructor	-0.006	-0.082**
	(0.010)	(0.039)
Non-Role-Model Instructor	-0.006	0.007
	(0.009)	(0.035)
Student Age	0.002	-0.038**
	(0.004)	(0.016)
Lives in Dorm	0.001	0.008
	(0.005)	(0.021)
Freshman	0.021*	0.028
	(0.011)	(0.044)
Sophomore	0.016**	0.019
	(0.006)	(0.027)
Junior	0.009**	0.021
	(0.004)	(0.016)
Constant	0.879***	3.749***
	(0.091)	(0.367)
N	57,147	57,147
$\beta_1 + \beta_2 = 0$ test P-value	0.797	0.788
Student FEs	Yes	Yes
Class FEs	Yes	Yes
Course x Race FEs	Yes	Yes

Estimates obtained from equation (1). The unit of observation is a student-class. Only students in must-take classes who received a midterm grade are included in the regression. Race-Matched Instructor is an indicator equal to one if the student and instructor have the same race. Non-Role-Model Instructor is an indicator equal to one if the student's age is within 10 years of, or greater than, their instructor's age. The outcome is the student's midterm grade, measured on a 4.0 scale. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 11
Differential Effects of a Race Match by Relative Student Age in *Must-Take Classes*
Outcome: Repeating the Course in the Future

	(1)
	Repeat in Future
Race Matched Instructor	-0.021***
	(0.008)
Race Matched x Non-Role-Model Instructor	0.013*
	(0.008)
Non-Role-Model Instructor	0.004
	(0.007)
N	62,308
$\beta_1 + \beta_2 = 0$ test P-value	0.418
Controls	Yes
Student FEs	Yes
Class FEs	Yes
Course x Race FEs	Yes

Estimates obtained from equation (1). The unit of observation is a student-class. Only students in must-take classes from Fall 2012-Fall 2017 are included in the regressions. Race-Matched Instructor is an indicator equal to one if the student and instructor have the same race. Non-Role-Model Instructor is an indicator equal to one if the student's age is within 10 years of, or greater than, their instructor's age. The outcome is an indicator equal to one if the student will repeat the course in the future. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 12
The Impact of Race Matches on Students' Graduation Outcomes

	(1)	(2)
	On-Time Graduation	Graduation GPA
Share of Race-Matched Role Model Instructors	0.365***	0.072
	(0.056)	(0.076)
Share of Race-Matched Non-Role-Model Instructors	-0.021	-0.203
	(0.096)	(0.176)
Student's Age at Entry	-0.005***	0.009***
	(0.001)	(0.002)
Number of Semesters in Dorm	0.012***	0.025***
	(0.003)	(0.004)
Female Student	0.056***	0.102***
	(0.013)	(0.017)
Asian Student	0.077	-0.068
	(0.050)	(0.063)
Black Student	-0.070***	-0.413***
	(0.017)	(0.022)
Hispanic Student	0.025	-0.037
	(0.032)	(0.043)
Other Race Student	-0.010	-0.019
	(0.037)	(0.062)
Constant	0.398***	2.976***
	(0.028)	(0.044)
N	8,140	5,391
Semester x Rank x Major FEs	Yes	Yes

Estimates obtained from equation (6). The unit of observation is a student. Students that took at least one must-take class enter. Students that graduate with a double major are excluded. In column 1 (2), the outcome is an indicator equal to one if the student graduated in four (five) years, adjusted by rank at entry. In column 3, the outcome is the student's final cumulative weighted GPA in classes taken at the University. Semester x Rank x Major fixed effects are included, where Semester refers to the semester at time of entry, Rank refers to rank at time of entry, and Major refers to the student's last major. Standard errors clustered at the student level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 13
Effect Heterogeneity for Students in STEM vs. Non-STEM Programs in *Must-Take Classes*

	STEM		Non-STEM	
	(1)	(2)	(3)	(4)
	Passed the Class	Final Grade	Passed the Class	Final Grade
Race-Matched Instructor	0.011	0.042	0.020***	0.182***
	(0.012)	(0.041)	(0.007)	(0.037)
Race-Matched × Non-Role-Model Instructor	-0.028**	-0.071	-0.017**	-0.100***
	(0.011)	(0.045)	(0.008)	(0.038)
Non-Role-Model Instructor	0.016	0.018	0.010	0.035
	(0.011)	(0.040)	(0.008)	(0.035)
Observations	28,783	28,783	39,496	39,496
$\beta_1 + \beta_2 = 0$ test P-value	0.219	0.597	0.672	0.059
Controls	Yes	Yes	Yes	Yes
Student FEs	Yes	Yes	Yes	Yes
Class FEs	Yes	Yes	Yes	Yes
Course x Race FEs	Yes	Yes	Yes	Yes

Estimates obtained from equation (1). The unit of observation is a student-class. In columns 1 and 2, only students in must-take classes enrolled in STEM majors are included. In columns 3 and 4, only students in must-take classes enrolled in non-STEM majors are included. Race-Matched Instructor is an indicator equal to one if the student and instructor have the same race. Non-Role-Model Instructor is an indicator equal to one if the student's age is within 10 years of, or greater than, their instructor's age. The outcome is the student's final grade, measured on a 4.0 scale. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 14
Effect Heterogeneity by Instructor Value Added

	Low	Med.	High
	(1)	(2)	(3)
		Final Grade	
Race-Matched Instructor	0.240***	0.104**	-0.076
	(0.083)	(0.044)	(0.079)
Race-Matched × Non-Role-Model Instructor	-0.224**	-0.118***	0.175*
	(0.097)	(0.042)	(0.091)
Non-Role-Model Instructor	0.143*	0.011	0.015
	(0.084)	(0.037)	(0.092)
Observations	14,281	31,149	14,457
$\beta_1 + \beta_2 = 0$ test P-value	0.893	0.793	0.347
Controls	Yes	Yes	Yes
Student FEs	Yes	Yes	Yes
Class FEs	Yes	Yes	Yes
Course x Race FEs	Yes	Yes	Yes

Estimates obtained from equation (1). The unit of observation is a student-class. In column 1, only students in classes led by instructors with low value added enter, i.e., instructors who are in the bottom 25% of the value-added distribution. In column 2, only students in classes led by instructors with medium value added enter, i.e., instructors who are between the 25th and 75th percentile of the value-added distribution. In column 3, only students in classes led by instructors with high value added enter, i.e., instructors who are in the top 25% of the value-added distribution. The outcome is the student’s final grade, measured on a 4.0 scale. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Appendix Table 1
Test for Student Selection Based on Instructor Characteristics in *Required May-Take Classes*

Panel A:

	(1)	(2)	(3)	(4)
	Black Instructor	White Instructor	Asian Instructor	Hispanic Instructor
%Black Students in the Class	0.033***			
	(0.012)			
%White Students in the Class		0.060***		
		(0.017)		
%Asian Students in the Class			0.105	
			(0.077)	
%Hispanic Students in the Class				0.002
				(0.029)
Constant	0.031***	0.815***	0.058***	0.036***
	(0.004)	(0.012)	(0.002)	(0.002)
N	10,155	10,155	10,155	10,155
Course x Term FEs	Yes	Yes	Yes	Yes

Panel B:

	(1)	(2)	(3)	(4)
	In Past Classes, Average Grades Assigned by the Instructor to …			
	Black Students	White Students	Asian Students	Hispanic Students
%Black Students in the Class	0.034			
	(0.022)			
%White Students in the Class		-0.006		
		(0.015)		
%Asian Students in the Class			0.183*	
			(0.107)	
%Hispanic Students in the Class				0.103**
				(0.045)
Constant	2.535***	3.093***	3.128***	2.955***
	(0.008)	(0.010)	(0.006)	(0.005)
N	9,199	9,262	8,019	8,824
Course x Term FEs	Yes	Yes	Yes	Yes

Appendix Table 1 Continued

Panel C:

	(1)	(2)	(3)	(4)
		Instructor's Age …		
	Under 30	30 to 40	40 to 50	Over 50
%Students 20 to 30 in the class	-0.075***	-0.021	0.032	0.065***
	(0.018)	(0.023)	(0.023)	(0.024)
%Students 30 to 40 in the class	-0.129***	-0.006	0.055	0.080**
	(0.027)	(0.038)	(0.036)	(0.037)
%Students 40 to 50 in the class	-0.153***	0.018	0.147***	-0.012
	(0.040)	(0.060)	(0.056)	(0.058)
%Students Over 50 in the Class	-0.201***	0.208***	0.042	-0.050
	(0.052)	(0.081)	(0.080)	(0.087)
Constant	0.193***	0.317***	0.219***	0.272***
	(0.013)	(0.017)	(0.016)	(0.017)
N	10,155	10,155	10,155	10,155
Course x Term FEs	Yes	Yes	Yes	Yes

Estimates obtained from equation (2). The unit of observation is a class. Only students in may-take classes which are required by their academic program but offered by more than one instructor are included in the regressions. In Panel C, the omitted category consists of students less than 20 years old. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Appendix Table 2
Differential Effects of a Race Match by Relative Student Age
Using Sample of *Must-Take Classes* Taught by the Same Instructor in Three Consecutive Semesters

	(1)	(2)	(3)
	Completed the Class	Passed the Class	Final Grade
Race-Matched Instructor	0.010	0.051	0.487***
	(0.011)	(0.035)	(0.119)
Race-Matched × Non-Role-Model Instructor	-0.002	-0.057**	-0.191**
	(0.018)	(0.023)	(0.096)
Non-Role-Model Instructor	0.012	0.028	0.043
	(0.015)	(0.019)	(0.075)
Student's Age	0.009*	-0.007	-0.051*
	(0.005)	(0.007)	(0.029)
Lives in Dorm	-0.008	0.003	0.054
	(0.006)	(0.008)	(0.037)
Freshman	0.007	0.059***	0.142
	(0.013)	(0.021)	(0.090)
Sophomore	-0.001	0.005	0.015
	(0.008)	(0.012)	(0.052)
Junior	0.001	0.006	0.050*
	(0.006)	(0.007)	(0.029)
Constant	0.765***	1.060***	3.936***
	(0.122)	(0.160)	(0.670)
N	19,665	16,354	16,354
$\beta_1 + \beta_2 = 0$ test P-value	0.670	0.888	0.045
Student FEs	Yes	Yes	Yes
Class FEs	Yes	Yes	Yes
Course x Race FEs	Yes	Yes	Yes

Estimates obtained from equation (1). The unit of observation is a student-class. Only students in must-take classes led by instructors who offered the course in at least three consecutive semesters are included in the regressions. Race-Matched Instructor is an indicator equal to one if the student and instructor have the same race. Non-Role-Model Instructor is an indicator equal to one if the student's age is within 10 years of, or greater than, their instructor's age. Outcomes are the same as those shown in Table 6. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Appendix Table 3
Differential Effects of a Race Match by Relative Student Age Using Alternate Sample of *Must-Take Classes* Required by Students' Last Major

	(1)	(2)	(3)
	Completed the Class	Passed the Class	Final Grade
Race-Matched Instructor	0.005	0.016**	0.103***
	(0.005)	(0.006)	(0.027)
Race-Matched × Non-Role-Model Instructor	-0.004	-0.018***	-0.060**
	(0.006)	(0.006)	(0.028)
Non-Role-Model Instructor	-0.002	0.011*	0.018
	(0.005)	(0.006)	(0.025)
Student's Age	0.005**	-0.004	-0.014
	(0.002)	(0.003)	(0.012)
Lives in Dorm	-0.000	0.005	0.024
	(0.003)	(0.004)	(0.016)
Freshman	0.008	0.020**	0.059
	(0.006)	(0.009)	(0.037)
Sophomore	0.001	0.018***	0.037*
	(0.004)	(0.005)	(0.021)
Junior	0.000	0.009***	0.042***
	(0.002)	(0.003)	(0.012)
Constant	0.856***	1.022***	3.340***
	(0.052)	(0.064)	(0.281)
N	72,213	66,858	66,858
$\beta_1 + \beta_2 = 0$ test P-value	0.787	0.764	0.198
Student FEs	Yes	Yes	Yes
Class FEs	Yes	Yes	Yes
Course x Race FEs	Yes	Yes	Yes

Estimates obtained from equation (1). The unit of observation is a student-class. Students in classes that are required by their last observed major and taught by only one instructor enter. Race-Matched Instructor is an indicator equal to one if the student and instructor have the same race. Non-Role-Model Instructor is an indicator equal to one if the student's age is within 10 years of, or greater than, their instructor's age. Grade outcomes are the same as those shown in Table 6. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Appendix Table 4
Main Results Controlling for Whether the Student had Previously Taken a Course from the Current Instructor

	(1)	(2)	(3)
	Completed the Class	Passed the Class	Final Grade
Race-Matched Instructor	0.007	0.015**	0.117***
	(0.005)	(0.007)	(0.027)
Race-Matched x Non-Role-Model Instructor	-0.007	-0.023***	-0.087***
	(0.006)	(0.007)	(0.029)
Non-Role-Model Instructor	0.003	0.013**	0.033
	(0.006)	(0.007)	(0.026)
Previously Taken Instructor	0.054***	0.014***	0.080***
	(0.003)	(0.003)	(0.012)
N	74,681	68,643	68,643
$\beta_1 + \beta_2 = 0$ test P-value	0.998	0.340	0.366
Controls	Yes	Yes	Yes
Student FEs	Yes	Yes	Yes
Class FEs	Yes	Yes	Yes
Course x Race FEs	Yes	Yes	Yes

Estimates obtained from equation (1). The unit of observation is a student-class. Only students in must-take classes are included in the regressions. Race-Matched Instructor is an indicator equal to one if the student and instructor have the same race. Non-Role-Model Instructor is an indicator equal to one if the student's age is within 10 years of, or greater than, their instructor's age. Previously Taken Instructor is an indicator equal to one if the student had previously taken a course from the instructor of the class. Outcomes are the same as those shown in Table 6. Standard errors clustered at the class level are presented in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.