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ABSTRACT

Detailed administrative data from a large and diverse community college are used to examine if academic performance depends on whether students are the same race or ethnicity as their instructors. To identify racial interactions and address many threats to internal validity we estimate models that include both student and classroom fixed effects. Given the large sample sizes and computational complexity of the 2-way fixed effects model we rely on numerical algorithms that exploit the particular structure of the model's normal equations. Although we find no evidence of endogenous sorting, we further limit potential biases from sorting by focusing on students with restricted course enrollment options due to low registration priorities, students not getting first section choices, and on courses with no within-term or within-year racial variation in instructors. We find that the performance gap in terms of class dropout rates, pass rates, and grade performance between white and underrepresented minority students falls by 20-50 percent when taught by an underrepresented minority instructor. We also find these interactions affect longer term outcomes such as subsequent course selection, retention, and degree completion. Potential mechanisms for these positive interactions are examined.

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1. Introduction

The achievement gap between historically underrepresented minority students and non-minority students is one of the most persistent and vexing problems of the educational system in the United States. African-American, Latino and Native-American students have substantially lower test scores, grades, high school completion rates, college attendance rates, and college graduation rates than non-minority students.[1] Fryer and Levitt (2006)and Fryer (2011) document that, for African-Americans, achievement gaps start to appear in elementary school and persist throughout primary and secondary education, while Reardon and Galindo (2009)find that, for Hispanics-, achievement gaps are already substantial at the start of kindergarten.[2] The empirical evidence presented by Fry (2002) and Arcidiacono et al. (2011) suggests that similar gaps exist at post-secondary institutions. Ultimately these gaps translate into substantially lower completion rates for African-Americans and Latinos compared to non-minorities. A major concern is that, in spite of substantial publicity and some affirmative action, the gap has not shrunk over the last two decades, which contrasts sharply with trends in other educational disparities such as the gender gap.[3] Such persistent disparities in educational attainment may have major implications for income and wealth inequality across racial and ethnic

[1] See U.S. Department of Education (2010).

[2] Fryer and Levitt (2013) find no black/white gap in cognitive abilities at age 8 to 12 months. An extensive literature examines the underlying causes of the black/white achievement gap among children and its persistence even after controlling for a wide range of individual and family characteristics (e.g., see Jencks and Phillips 1998). A few examples of recent explanations with empirical support include segregation (Card and Rothstein 2007), attending schools with higher black enrollment shares and less teacher experience (Hanushek and Rivkin 2008), permanent income disparities (Rothstein and Wozny 2011), lower school quality (Fryer and Levitt 2004), and differences in social norms (Austen-Smith and Fryer, 2005). For Hispanics, Reardon and Galindo (2009) find that the gaps in reading and math skills are largest for Hispanic children where English is not spoken at home, but that these children also show the greatest relative gains in the early years of schooling.

[3] See e.g. Fryer and Levitt (2006).

groups.[4] It is therefore imperative to study the sources of the racial achievement gap and to evaluate the effectiveness of potential policy interventions.

A common, though hotly debated, policy prescription is to expand the representation of minority instructors at all levels of the educational system. Indeed, there is a general lack of minority instructors, especially at the post-secondary level: only 9.6 percent of all full-time instructional faculty at U.S. colleges are black, Latino or Native American, while these groups comprise one-third of the college-age population and an even higher percentage of children.[5] As argued by many social scientists, this imposes severe limits on the availability of role models, increases the likelihood of “stereotype threats” and discrimination against minority students, and restricts exposure to instructors with similar cultures and languages.

In this paper we offer the first systematic empirical study of minority interactions between students and instructors at the post-secondary education level. We test whether underrepresented minority students experience significant achievement gains from being taught by an underrepresented minority professor. "Underrepresented minority", which we use interchangeably with "minority" below, includes African-Americans, Hispanics, and Native Americans/Pacific Islanders, but not Asian-Americans.[6] These questions are examined using a novel and unique administrative dataset with detailed demographic information on instructors as well as students from a large and ethnically diverse community college. Our data contain comprehensive background information on instructors and students for each class, students’ course-level academic outcomes, and long-term outcomes such as majors, retention, degree completion, and transfers to 4-year

[4] Such arguments are made in e.g. Altonji and Blank (1999), Card (1999), and Jencks and Phillips (1998).
[5] See U.S. Department of Education (2010).
[6] This is the common definition used for "underrepresented minority" in California public higher education.

colleges. We are also able to match student-course-level data to administrative data on all registration attempts and waitlists by students at the college, allowing us to examine whether students get their first choice among sections.

In addition to providing general evidence on the importance of social interactions by race and ethnicity, our study is also the first to focus on the community college system. The lack of previous research using data from community colleges is somewhat surprising given that they enroll nearly half of all students attending public universities. Since community colleges, in addition to providing workforce training, serve as an important gateway to 4-year colleges, they can be seen as a crucial part of the post-secondary educational system in the United States. In fact, in some states, including California, nearly half of all students attending a 4-year college previously attended a community college.[7] With recent calls for major expansions in enrollments and provision of 4-year transfer courses, one can expect that community colleges will gain further importance.[8] Policy interventions targeting community colleges are therefore likely to have major effects on the educational system as a whole.

It is well known that random assignment of students to classes does not occur at community colleges or 4-year universities outside of the military post-secondary educational system.[9] We therefore employ several empirical strategies to rule out the possibility that the estimates are driven by omitted variable biases, to explore the external validity of our results, and to investigate the channels through which our estimated

[7] See U.S. Department of Education (2010); CCCCO (2009); Sengupta and Jepsen (2006).
[8] For example, President Obama has proposed an unprecedented funding increase for community colleges that aims to boost graduates by 5 million students by 2020. In California, transfers from community colleges to the California State University (CSU) system are projected to increase by 25 percent over the next decade (California Postsecondary Education Commission 2010).
[9] Random assignment takes place at the U.S. Air Force Academy that provides undergraduate education for officers in the U.S. Air Force (Carrell, Page, and West 2010).

reduced-form effects operate. Our basic empirical approach is built on a regression model in which the parameter of interest is the differential effect between minority and non-minority students of being assigned to a minority-instructor in the same class. This answers the question of whether minority students experience gains relative to non-minority students from being taught by minority instructors. The focus on estimation of these interaction effects from panel data such as ours permits tremendous flexibility in the types of specifications one can estimate. In particular, the explanatory variable of interest varies both within student and within classroom, allowing us to estimate models that simultaneously include student and classroom fixed effects. This eliminates biases coming from student specific differences common across courses and classroom specific differences common across classmates.[10] Including classroom fixed effects leads to standardizing grade outcomes, since we are only using within-classroom differences among students who complete the same assignments, take the same exams, and are subject to the same grading policies. Furthermore, our two-way fixed effects specification with individual and class fixed effects controls for the possibility that minority and non-minority students enroll in courses or subjects with more lenient grading policies. Given the sample size – we observe over 30,000 students in nearly 21,000 classes – estimation of this model by conventional algorithms is computationally infeasible. To address this problem, we conduct the first application of an algorithm that has been applied to the estimation of firm and worker fixed effects with large administrative data to the estimation of student and teacher fixed effects.[11]

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[10] Here and subsequently we use the term "class" or "classroom" to refer to a particular offering or section of a course with a specific instructor during some term, such as "Principle of Microeconomics: ECON-100". Hence, a "class" or "classroom" is uniquely defined by course title, section, and term.
[11] See for example Abowd, Kramarz, and Margolis (1999) and Abowd, Creecy, and Kramarz (2002).

While our empirical model addresses many of the potential threats to internal validity, we cannot directly control for differential sorting across minority student groups that may arise if, for example, highly motivated minority students systematically sort into minority-taught classes while highly motivated non-minority students do not. However, with an appropriate set of observable variables that is highly correlated with unobserved student abilities, such as a student's past academic performance, this hypothesis of differential sorting is testable. Implementation of such a test using a rich set of observables does not uncover any evidence of differential sorting. Nevertheless, we exploit the institutional features at our community college to generate samples of students in which the incidence of endogenous sorting of students to instructors is minimized. We take advantage of the registration priority system at the community college and focus on students with limited class enrollment choices. Given the intense competition for classes created by negligible tuition, absence of admissions requirements, and desirable location of the college, students with the lowest registration priority status have severely restricted class enrollment choices. Registration attempt data confirm the limited choices of these students (only 55 percent get their first section choice) and allow us to further refine the sample. We also estimate our model from a sample of courses in which students have no choice over instructor's race within a term or even academic year, thus ruling out the possibility of sorting within that term or year by construction.

We find that the minority achievement gap is smaller in classes taken with minority instructors for several course outcome measures. Minority students obtain better grades, are less likely to drop a course, are more likely to pass a course, and are more likely to have a grade of at least a B. These gaps are reduced by 20-50percent with a minority instructor and translate into longer-run impacts on taking additional courses in subjects, major choice, retention, and degrees. Effects on dropping a course in the first few weeks, long-term outcomes, and performance in more objectively graded courses such as those commonly using multiple-choice exams and math courses, suggest that students are reacting to the race and ethnicity of the instructor rather than the other way around. We find evidence of both positive role model effects, with minority students performing better with minority instructors, and negative influences, with non-minority students doing worse with minority instructors.

Our paper is related to a number of studies, most notably Dee (2004, 2005, 2007) and Ehrenberg, Goldhaber and Brewer (1995), that use data from the elementary and 8th grade educational levels to estimate race and ethnicity interactions between students and teachers. They find some evidence of positive student-teacher interactions by race and gender. Our paper is also related to a small, but growing literature that focuses on gender interactions between students and instructors at the post-secondary level. Similar to our work, these studies rely increasingly on high-quality administrative student panel data that can be matched to instructor-level data. They tend to conclude that female students perform relatively better when matched to female instructors (e.g. Bettinger and Long 2005; Hoffmann and Oreopoulos 2009).[12] A recent study by Carrell, Page, and West (2010), which takes advantage of the random assignment of students to classrooms at the U.S. Air Force Academy, also finds that female students perform better in math and science courses with female instructors. None of these previous studies, however,

[12] A larger literature studies gender interactions at the primary or secondary school level. The findings are generally mixed (see for example, Nixon and Robinson 1999, Ehrenberg, Goldhaber, and Brewer 1995, Dee 2007, Holmlund and Sund 2005, Carrington, Tymms and Merrel 2008, Lahelma 2000, and Lavy and Schlosser 2007).

examine the impact of an instructor's minority status, race or ethnicity on student outcomes at the post-secondary education level, due to not being able to obtain race information on instructors and the lack of underrepresented minority faculty at more selective colleges. This might be an important omission in the literature, as the effects of minority faculty on minority students may be larger due to the sizeable racial achievement gap and similarities in culture, language and economic backgrounds. In addition, measures of racial inequality in education, income and other outcomes have not decreased over the last two decades, in sharp contrast to corresponding measures of gender inequality. Our data also allow us to explore interaction effects on a more comprehensive set of course-level and long-term outcomes compared to previous studies.

The rest of the paper proceeds as follows: Section 2 starts by providing some institutional background, and then describes and summarizes the data. The next section introduces our econometric framework. Section 4 presents evidence on student sorting and the main results on racial interactions in educational outcomes. The final section concludes.

2. Data

2.1 Institutional Background

Our analysis is based on administrative data from De Anza College, a large community college that is located in the San Francisco Bay Area. It is part of the California Community College system, which is the largest higher educational system in the United States with 110 colleges and 2.9 million students per year. De Anza College has an average total enrolment of 22,000 students per year. It has a larger share of minority students than the nationally representative community college, reflecting the diversity of Northern California. The College is on the quarter system, and the majority of classes are restricted to 50 or fewer students. The tuition at De Anza College is $17 per unit (roughly $850 per year in tuition and fees) with a large percentage of students receiving fee waivers because of financial need. Similar to all community colleges in California it has open enrolment – anyone with a high school diploma or equivalent is automatically admitted.

2.2 Registration Priority System

Open enrolment, very low tuition costs, mandated small class sizes, and its location in the San Francisco Bay Area create intense competition for courses at De Anza College. Because of the general excess demand for courses, the College has established a strictly enforced registration priority system which determines the day on which students are allowed to register over an eight-day period. Registration priority is determined by whether the student is new, returning or continuing, the number of cumulative units earned at De Anza College, and enrolment in special programs.[13] It does not depend on past academic performance. Incoming students and students who have taken a break away from the college have the lowest priority status. Priority status improves for continuing students by cumulative unit blocks.

[13] We remove students enrolled in special and often minority-student focused programs, such as SLAM, STARS, and SSRC. These students receive special registration priority status even if they are new or returning students.

A student's registration priority has a large impact on his or her choice of classes.[14] Conversations with college administrators revealed that students with a low ranking on course-priority lists have severely limited choices in instructors. As a consequence, for a particular course that has multiple class offerings these students should be expected to have little control over the instructor with whom they are matched. We confirm this anecdotal evidence by analyzing detailed registration attempt and wait-list data from the college. We find that among students with a low registration priority, only 54.9 percent of the course sections in which students first attempt to register result in an actual enrolment, compared with approximately 74.5 percent for students with a higher registration priority We also find higher probabilities of being placed on wait lists for first registration attempts among low-registration priority students compared to students with higher registration priorities (7.2 percent compared with 3.4 percent).

2.3 Data Set

Matching several administrative datasets from the college, National Student Clearinghouse data, and data from other sources, we are able to examine an extensive set of course and long-term outcomes as well as detailed demographic characteristics for every student registered at the community college from fall quarter of 2002 to spring quarter of 2007. The data on course outcomes record grades, course credits, and course dropout behaviour for every class offered by De Anza College over the five-year period. We are able to match them to detailed data on demographic characteristics of instructors, such as race, ethnicity, age, and gender for every class. To our knowledge, this is the first

[14] In personal conversations with college administrators we have learned that students often register for classes as soon as they are allowed to through the system because of the intense competition for courses.

dataset that contains detailed information about instructors' race together with student class outcomes on the post-secondary education level. A student's registration priority together with any of her registration attempts is recorded at the beginning of each quarter.[15] Hence, the course-level dataset allows us to match students to classes that students enrolled in before their first day of the term, regardless of whether they completed the class or not.

Administrative data from the college provide information on majors together with all associate and vocational degrees received through summer 2010 for each student enrolled over the five-year period. We obtain data on an additional long-term outcome – transfers to 4-year colleges – by linking National Student Clearinghouse data through summer 2012 to all of the students enrolled during the five-year period.

2.4 Sample Restrictions and Summary Statistics

We first exclude recreational courses, such as cooking, sports and photography, orientation courses, and summer courses from our analysis. In the main sample we also exclude courses that have an average enrolment per session of less than 15 students and small academic departments to minimize computation without losing identification power. To remove concerns about local community residents taking classes for recreational purposes and to focus on the general college-age population, we exclude students who are over 35 years old in the main sample. Only 2.4 percent of all student-class observations are for small courses, 1.2 percent of observations are for courses from

[15] The registration attempt data record the exact date and time the registration attempt was made together with the outcome, such as whether the attempt was successful or ended on a waitlist.

a small academic department, and 9.2 percent of observations are for older students. The resulting sample consists of 446,239 student-class observations.

Of the main sample, 29 percent of observations are from students with low registration priority status and 10 percent of student/class observations are from entering students (Panel A, Table 1). Another method of restricting choice among students is to include course-term or course-year combinations for which different sections are taught by different instructors, all of which share a particular minority status. Sixty-one percent of student/class observations have no variation in underrepresented minority status within quarters and 52 percent of student/class observations have no variation in underrepresented minority status within academic-years. In terms of types of courses in the main sample, we find that only 3 percent of student/class observations are in language courses and 6 percent are in video-delivered classes. We also find that 26 percent of observations are vocational courses, and 70 percent are courses that are transferable to University of California (UC) or California State University (CSU) campuses, reflecting the reputation of De Anza College of being a more academically oriented community college. We conduct sensitivity analyses with all of these types of courses below.

There are important differences in student outcomes across groups. White and Asian students have the highest average outcomes (Panel B, Table 1). Hispanics, African-American, and Native American, Pacific Islander and other non-white students are more likely to drop classes, are less likely to pass classes, receive lower average grades, and are less likely to receive a good grade (B or higher).[16] For most outcomes, these differences

[16] Students have to drop a class by the end of the second week of the quarter to avoid paying for the class and by the end of the third week to avoid getting a record of a grade. A GPA equivalent to a letter grade of a B is commonly used as a minimum threshold for qualification for admission to the University of California.

are large and statistically significant, documenting that the largest differences in academic outcomes take place along the underrepresented minority-non-underrepresented minority margin rather than along less aggregated measures of differences in race and ethnicity. Aggregating up these statistics for the underrepresented minority group yields a dropout rate of 28 percent. The average GPA is 2.6 (where 4.0 is equivalent to an A), and 57 percent of classes taken by students for letter grades receive a grade of B or higher. Of all underrepresented minority students who finish classes, the total pass rate is 83.5 percent. There also exist racial and ethnic differences in long-term outcomes. African-American, Latino and other underrepresented students have substantially lower retention rates, are less likely to obtain a degree from the community college, and are less likely to transfer to a 4-year college.

Panel C of Table 1 displays the racial and ethnic composition of the student body and instructors. White students comprise 28 percent of all students and Asians comprise 51 percent of students. Hispanic students represent the largest underrepresented minority group with 14 percent of all students. African-American students comprise 4 percent of students and Native American, Pacific Islanders, and other non-white students comprise 3 percent of students. Underrepresented minorities comprise 21 percent of the total student body. The racial distribution of instructors at the college differs substantially from the student distribution. 70 percent of instructors are white. In contrast, only 14 percent of instructors are Asian and 6 percent of instructors are Hispanic. Interestingly, the percentage of African-American instructors and Native American, Pacific Islander and other non-white instructors are slightly higher than their representation in the student body. The lack of minority instructors at De Anza College does not differ from the national pattern for all colleges. Roughly 10 percent of all college instructors are from underrepresented minority groups (U.S. Department of Education 2010). At De Anza College, 16 percent of instructors are from underrepresented minority groups.

3. Statistical Methodology

3.1 Basic Econometric Model

We now turn to the description of the econometric models for the student outcome variables, y_{ijkst}, such as course dropout behaviour and grade. We index students by i, instructors by j, courses by k, sections by s, and term (i.e. quarter) by t. Let min_stud_i and min_inst_j be indicator variables that are equal to one if student i and instructor j belong to an underrepresented minority group, respectively, and let X_{ijkst} and u_{ijkst} be vectors of observable and unobservable variables affecting outcomes. To test whether minority students gain from being taught by a minority instructor, a natural starting point is to consider the regression:

$$y_{ijkst} = \alpha_0 + \alpha_1 * min\_inst_j + X'_{ijkst}\beta + u_{ijkst}. \qquad (1)$$

for a sample of only minority students. It is not our preferred specification because average teaching abilities and grading standards of minority and non-minority instructors in the sample may not be the same, and it is therefore helpful to specify an empirical model that is estimated on the full sample which can allow for classroom fixed effects. We thus estimate the relative student-instructor interaction effect, α_3, from the regression:

$$\begin{aligned} y_{ijkst} &= \alpha_0 + \alpha_1 * min\_inst_j + \alpha_2 * min\_stud_i \\ &\quad + \alpha_3 * min\_inst_j * min\_stud_i + X'_{ijkst}\beta + u_{ijkst}. \end{aligned} \qquad (2)$$

The parameter of interest is α_3 and determines the difference in the minority-instructor effect between minority and non-minority students. It thus measures the extent to which minority gaps in the outcome variables depend on whether the students are assigned to a minority or a non-minority instructor. The parameter, α_3, is consistently estimated if $\operatorname{cov}(u_{ijkst}; interact_{ij}) = 0$, where $interact_{ij} = min\_inst_j * min\_stud_i$. Correlations between the interaction term and the unobserved component, however, may be caused by several factors we discuss below. We therefore impose the following structure on the error u_{ijkst}:

(3) $$u_{ijkst} = \gamma_i + \phi_{kst} + \varepsilon_{ijkst}.$$

where γ_i and ϕ_{kst} are student and classroom fixed effects, respectively. Dropping student- and class-level variables from equation (2) that are multicollinear with either of the fixed effects, we obtain our preferred empirical model:

(4) $$y_{ic} = \alpha_3 * min\_stud_i * min\_inst_c + \gamma_i + \phi_c + u_{ic}$$

where we have replaced the combination of the indices k, s, t by a classroom index c and where we have indexed the minority-instructor dummy by c rather than j.

The focus on the interaction term of students' and instructors' minority status allows us to identify individual and classroom fixed effects, thereby overcoming many threats to the internal validity of estimates that have plagued the literature on student-teacher interactions. Importantly, our specification implicitly controls for instructor fixed effects and minority-specific course fixed effects since a student can enrol only in one section per course, and since each class is taught by exactly one instructor. The former controls for the possibility that minority students take courses from instructors who have systematically different grading policies from other instructors, while the latter controls for selection by comparative advantage where minority students are drawn to courses that are a particularly good match or in which minority instructors are relatively overrepresented. A further advantage of including classroom fixed effects is that they avoid the need to rely on data with standardized testing procedures across classrooms since within the same classroom students are taking exactly the same tests. Unless instructors discriminate against certain groups of students, consciously or subconsciously, students within a class are subject to identical grading criteria.[17] These issues are specific examples of classroom level shocks (i.e. factors that are unobserved by the econometrician, that vary at the classroom level, and that affect student performance). It is therefore essential to only compare academic performances of minority and non-minority students who enrol in the same class, which subjects them to the same class-level shocks such as an instructor's teaching performance or philosophy, the time of day, or external disruptions. Finally, we include individual fixed effects γ_i in our regressions to control for <u>absolute</u> sorting that takes place if students taking classes from minority instructors are systematically different from those who do not, irrespective of their minority background.

While our specification addresses many of the potential threats to internal validity, we cannot directly control for differential sorting across minority student groups that may arise due to correlations between the unobserved component u_{ic} and the interaction term. Such correlations exist if for example highly motivated minority students systematically sort into minority-taught classes, while highly motivated non-

[17] The possibility that student-instructor interactions may exist because instructors react to students rather than vice versa is explored in detail in section 4.6. This issue may arise, however, even if tests are standardized and if students are randomly assigned to instructors. It is thus not a matter of omitted variable bias, but a matter of interpreting the reduced-form coefficient α_3 correctly.

minority students systematically sort into non-minority-taught classes. In this case the following inequality will apply:

(5)
$$E[u_{ic} \mid min\_stud_i = 1, min\_inst_c = 1] - E[u_{ic} \mid min\_stud_i = 0, min\_inst_c = 1]$$
$$\neq E[u_{ic} \mid min\_stud_i = 1, min\_inst_c = 0] - E[u_{ic} \mid min\_stud_i = 0, min\_inst_c = 0] \cdot$$

The differences on each side of the inequality are "minority gaps" in unobserved components. The inequality can be replaced by an equality only if these gaps do not depend on the minority status of the instructor, which is the case if there are minority gaps that persist across all classes, independent of instructor characteristics. This type of gap is implicitly controlled for in our empirical model through the inclusion of individual fixed effects and the estimation of what is essentially a difference-in-difference.

The hypothesis of differential sorting is testable if one has access to some measurable characteristics, x_{ic}, that are highly correlated with u_{ic}. Consider minority-specific classroom averages of x_{ic}, denoted $\overline{X_{mc}}$, where $m \in \{0,1\}$ is an index equal to one if the average is computed for minority-students and zero if it is computed for non-minority students. Since a classroom is associated with exactly one instructor minority status, these averages are the empirical counterparts of the conditional expectations in equation (5). We can then test for differential sorting by estimating a difference-in-difference model:

(6)
$$\overline{X_{mc}} = \delta_1 * min\_inst_c + \delta_2 * \mathrm{I}_m + \delta_3 * min\_inst_c * \mathrm{I}_m + \nu_{mc} \, .$$

where I_m is a dummy variable equal to one if $m = 1$ and zero otherwise, and δ_3 is an empirical estimate of the difference-in-difference in equation (5), with the observable measure, x_{ic}, replacing the unobserved component, u_{ic}. Hence, δ_3 quantifies the extent to which minority gaps in an observable variable, x_{ic}, vary across classes that are taught by instructors of different minority groups. Clearly, an estimate of δ_3 is only helpful in testing for differential sorting if x_{ic} is strongly related to u_{ic}. Given the richness of our data, we are able to use several variables, such as past academic performance, age and gender, as measureable characteristics to estimate a large set of "sorting regressions" such as equation (6).

By including classroom fixed effects we implicitly control for systematic differences in subject or course choices and associated grading differences between minority and non-minority students. Differential sorting thus is an issue if it takes place across class offerings of a course, which may happen if there is unrestricted student choice of classes and multiple sections offered for the same course in the same term. To address these remaining concerns we estimate specifications in which the sample of students and courses is chosen to minimize the possibility of differential sorting across classes. We estimate equation (4) using a sample of students who have the lowest registration priority status, samples that rule out variation in instructors' minority status across classes within course-term or course-year, and a sample of students who do not obtain their first section of choice identified by the registration attempt data.

We estimate this model for five different student course outcome variables. The first four are a dummy variable for whether a student drops the course by the first three weeks of the quarter, a dummy variable for whether a student passes the course conditional on finishing it, a course grade variable that is normalized to have mean zero and unit standard deviation within a course, and a dummy variable for whether the student has a grade above a B-. All of these outcomes relate to a student's academic achievement in a particular course. Our data also allow an exploration of whether minority interactions are relevant for a student's future curriculum. We therefore generate a fifth outcome variable that records whether a student takes another course in the same subject in the next quarter, which cannot be directly influenced by the instructor.

In the main specifications, we identify the relative effect of an underrepresented minority student being assigned to an underrepresented minority instructor (i.e. African-American, Hispanic, Native American, Pacific Islander, or other non-white). This specification implicitly assumes that underrepresented minority students are influenced by any underrepresented minority instructor (e.g. Hispanics react equally whether matched to a Hispanic or black instructor) and by a similar amount. The alternative case of interaction effects only when a student is matched with a same race/ethnicity instructor takes us in the other direction, assuming 1) no effect across minority types (e.g. no interaction effect for Hispanic students matched to Black instructors or vice versa), and 2) the performance gap from white and black students being assigned to a black instructor is the same as that for Hispanic and black students assigned to a black instructor. As discussed below, when we estimate a full set of interactions for each student type and each instructor type we find evidence against both these assumptions, and therefore estimate interaction effects with any minority instructor for our baseline results. Similar results are obtained with the alternative specification and are displayed in Appendix Table 3.

3.2 Estimation of Two-Way Fixed Effect Model for Course Outcomes

Estimation of two-way fixed effects models with unbalanced panel data becomes computationally infeasible with large data sets. With more than 30,000 students and over

20,000 classrooms in our data, model parameters cannot be estimated directly by OLS. Since our data set is a non-balanced panel, conventional within transformations are not possible, either. We thus rely on recent advances in the estimation of firm-and worker fixed effects from administrative data. The computational algorithms used to estimate two-way fixed effects models with high-dimensional sets of dummy variables generally rely on the fact that each individual only contributes to the identification of a subset of the fixed effects.[18] In our example, each student only contributes to the identification of the classrooms she or he visits at one point. This implies that normal equations involve block-diagonal ("sparse") matrices whose inversion is much less difficult than the inversion of non-sparse matrices. In practice, one performs a within-transformation in a first step to eliminate individual fixed effects, and then solves the remaining normal equations using matrix-inversion schemes that exploit the block-diagonal structure of the remaining matrices.[19]

3.3 Bounds on Grades

Estimation of the econometric models for grade outcomes is possible only for the sample of students who complete the course. The propensity to finish a course might be affected by the variable of interest – the minority-status interactions between students and instructors within classrooms - as well. This creates a potential sample selection problem, formally described by the following set of equations:

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[18] The seminal paper in this literature is Abowd, Kramarz and Margolis (1999). Refinements have been developed by Abowd, Creezy and Kramarz (2002) and Andrews et al (2008). Cornelissen (2008) has written a Stata-routine based on these algorithms.

[19] The literature estimating firm-and worker fixed effects also utilizes the fact that many workers never change firms, thus not contributing to identification of any of the firm fixed effects. This can further increase the speed of computation. In our example, we cannot apply this method since nearly all students take more than one class in the data and thus contribute to the identification of at least some classroom fixed effects.

(7) $$grade_{ic} = \alpha_1^{grade} * min\_stud_i * min\_inst_c + \gamma_i^{grade} + \phi_c^{grade} + u_{ic}^{grade}$$

(8) $$dropped_{ic} = \alpha_1^{dropped} * min\_stud_i * min\_inst_c + \gamma_i^{dropped} + \phi_c^{dropped} + u_{ic}^{dropped}$$

(9) $$grade_{ic} = (1 - dropped_{ic}) * grade_{ic}^{*}.$$

Equations (7) and (8) replicate equation (4) for the grade-outcome and the dropout-variable, while equation (9) accounts for the potential selection bias. OLS-estimates of the parameter of interest, α_1^{grade}, are biased conditionally on individual fixed effects if $\alpha_1^{dropped}$ is significantly different from zero. Correcting for sample selection using a Heckman-selection model is difficult in our case since any variable affecting dropout behavior arguably also affects potential grades limiting our ability to find an exclusion restriction. Furthermore, with the inclusion of classroom- and student fixed effects, estimates from reduced-form Probit equations required for a Heckit-procedure are biased. We thus estimate non-parametric bounds of α_1^{grade} following Lee (2009).[20]

In general, OLS-estimates are biased downward if minority students are less likely to drop the course when the instructor belongs to the minority group as well, and if the marginal students induced to stay come from the left tail of the grade distribution. The estimates are instead biased upward if the marginal students come from the right tail of the grade distribution. We can therefore estimate an upper (lower) bound of α_1^{grade} when applying OLS to a sample without the ($\alpha_1^{dropped}$ *100)-percent worst (best) minority students in classes taught by a minority instructor.

We therefore apply the following procedure: In the first step we estimate equation (8) for the dropout-variable. This provides us with an estimate of $\alpha_1^{dropped}$, the "minority

[20] See also Krueger and Whitmore (2002) and Hoffmann and Oreopoulos (2009) for a related application.

gap" in dropout behavior when the class is taught by a minority instructor. We then calculate the ($\alpha_1^{dropped}$ *100) percentile ($\left(1-\alpha_1^{dropped}\right)$*100 percentile) of the minority-student grade distribution for every class taught by a minority instructor and drop all minority students with a final grade lower (higher) than this percentile. Since we are focusing on selection due to the *relative* difference from having a minority instructor between minority and non-minority students, we do not need to trim marginal non-minority students. In the second step we use this restricted sample to estimate the same equation as in the first step, but with final grade replacing the dropout variable as the outcome. We also perform this algorithm by running the dropout-regressions course-by-course, therefore providing us with course-specific estimates of $\alpha_1^{dropped}$. As Lee (2009) shows, this procedure yields the tightest bounds on the parameter of interest if the outcome variable is continuous. We thus compute the bounds only for the grade variable, which is our only continuous outcome variable, while leaving the results for the discrete outcome "Passed Course" uncorrected.[21]

We interpret these bounds results as a robustness check rather than as the main part of our analysis. By the logic of minority instructors serving as role-models, one may expect that it is the lower-achieving minority students rather than the best students who are at the margin of dropping a class and who are induced not to do so because they share the minority status with their instructor. We test this assumption by estimating a version of equation (4) for the course dropout variable that allows for an interaction between the

[21] Strictly speaking, this variable is not continuous, either. For our application, this can be problematic because the grade distribution has mass-points at the lower and upper tail. Hence, if we trim the distribution at the x%-percentile, we might drop more than x% of the student/grade observations. We solve this problem by randomly drawing from the student/grade observations clustered at the mass-points in such a way that exactly x% of the distribution is trimmed.

minority interaction and prior GPA and reject the hypothesis that the minority interaction is stronger for those with a higher prior GPA.

3.4 Long-Term Outcome Models

In addition to estimating minority instructor-student interactions effects on subsequent subject course selection, we also examine effects on more aggregated performance indicators: Retention at the community college, obtaining an associates or vocational degree, and transferring to a 4-year college. As a consequence of aggregation that generates only one observation per student we cannot include either classroom or student fixed effects. Instead, we start with estimating a regression model for long-term outcomes that includes a rich set of controls for student and instructor, year dummies for the first term of enrolment, and the number of courses taken in the first term.[22] This specification is of the form of equation (2). In all regressions for aggregate outcomes we focus on the student-instructor interactions for entering students, mainly because they are automatically assigned to the lowest level on the registration priority list and have limited information their first term, but also because results would be confounded by dynamic accumulation effects otherwise.

To further address endogeneity concerns, we estimate two additional models. In the spirit of matching estimators, the first of these models include a set of fixed effects for each set of courses taken in the first term. Since students taking the exact same set of courses in their first term are assigned the same fixed effect we compare individuals that "look very similar" with respect to their behaviour at college entry. Variation in having a

[22] We use age, gender, financial aid receipt, educational goals at the time of application, free and reduced lunch rate of high school and private high school attendance as controls for student characteristics, and instructor's full- vs. part-time status, gender and age as controls for instructor characteristics.

minority instructor would result from students taking these courses in different terms or in some cases different sections.

The second approach follows Bettinger and Long (2005) and uses the average deviation in minority instructor shares from steady-state minority instructor shares by department as an instrumental variable. This instrument is arguably driven by exogenous variation from term to term (i.e. caused by sabbatical leaves, new hires, variability in the temporary lecturer pool, retirements, and variability in the number of section offerings). This variation is averaged across a student's course set and then used as an instrument for whether the student has a minority instructor in the first term.[23] We present estimates for the three specifications for all long-term outcomes.

4. Results

4.1 Evidence against Sorting

We use several strategies to rule out the possibility that our results are being driven by unobserved classroom-specific selection. With the inclusion of classroom and student fixed effects, the primary threat to validity arises from the possibility that classes where minority students perform better relative to non-minority students than usual are also classes with a minority instructor and that this effect is not due to the interaction itself. We first investigate whether there is evidence of non-random sorting by minority status using equation (6) for various background variables that are likely to be correlated with the unobserved ability term. We focus on the interaction coefficient, δ_3, measuring

[23] The instrumental variable is equal to the difference between the minority share of instructors in that term and department and the minority share of instructors in that department over all years (i.e. the steady-state minority instructor share for that department). For additional variation we follow Bettinger and Long (2005) and define separate steady-state minority instructor shares for fall, winter and spring quarters.

the extent to which the minority-gap in the outcomes varies across classes taught by minority and non-minority instructors and is thus an estimate of differential sorting.

Results using several different student background variables are presented in Table 2. Standard errors are clustered at the course-term-minority level.[24] We use the following four outcome variables, corresponding to the variable $\overline{X_{mc}}$ in equation (6): student age, gender, the cumulated number of courses, and the cumulated GPA prior to enrolment. As past GPA and present GPA are highly correlated, we view the last variable as a particularly good measure of a potential unobserved student component that might be related to differential selection. In particular, if the minority-non-minority gap of accumulated GPA prior to enrolment in the current course is different in classes that are taught by minority instructors, our assumption of no differential sorting is most likely violated.

We do not find evidence of sorting: None of the estimates are statistically significant at any conventional level. Furthermore, this insignificance is not driven by the imprecision of our estimates. Rather, point estimates fluctuate considerably as we explore the robustness of our estimates across sub-samples, indicating that we cannot detect any systematic or robust sorting patterns in the data.[25] Most importantly, minority gaps in accumulated GPA prior to course enrolment – a variable that is most likely to be highly correlated with unobserved student traits – do not depend on instructor race. In other words, we do not find evidence that high ability minority students are more likely to take

[24] We obtain similar results when standard errors are instead clustered at the instructor level (see Appendix Table 1). .

[25] We find that these results are robust with respect to the regression specification, the sample, and the type of variation in instructor minority status across different class offerings of a course. See Fairlie, Hoffmann and Oreopoulos (2011) for results.

minority-taught classes compared with high ability non-minority students. We interpret this as strong evidence in favour of our working hypothesis of no differential sorting.

4.2 Main Results

Estimates of the minority interactions between students and instructors for all five course outcomes using the full sample and a subsample of students who are low on the registration priority list are reported in Table 3. We also explore the sensitivity of results with respect to the set of fixed effects included in the econometric models. As we move along the columns, we increasingly restrict the variation used to identify our parameter of interest. Results from our preferred specification described in equation (4) which includes both student and classroom fixed effects are displayed in column (8) of the table. The other specifications considered in the table include minority-specific time fixed effects and a set of student and instructor controls (column 1), a specification that adds minority-specific course fixed effects (column 2), a specification with minority-specific course-time fixed effects (column 3), and specifications with student, classroom and instructor fixed effects (columns 4 to 7, respectively). Standard errors are clustered by instructor.[26]

There are significant minority interaction effects on student dropout behaviour and grade performance that are robust with respect to the sample used and the set of fixed effects included. Our main estimates indicate a reduction of the minority gap in course

[26] We follow Cameron and Miller's (2013) suggestion of adapting a conservative strategy by choosing larger clusters. A natural choice is to cluster on the instructor level since this is the level of the treatment variation in our interaction analysis. However, a potential problem with this strategy is that the majority of the instructors in our sample teach multiple classes. As a consequence, standard errors clustered at the instructor level depend directly on classroom fixed effects which are estimated with (small-sample) bias. It is therefore plausible to assume that our standard errors are inflated. We have also estimated all specifications with clustering standard errors at the classroom level. This reduces standard error estimates slightly, but does not affect overall conclusions. We report these alternative results for our main specifications in Appendix Table 2.

dropout behaviour when taught by a minority instructor by 2 to 3 percentage points and in student grades by 5 percent of a standard deviation. These results are robust when including instructor or classroom fixed effects or when using minority-course fixed effects, implying that they are not being driven by grading differences across classes or student sorting by comparative advantage into subjects and courses.[27] Our baseline model with both class and student fixed effects also indicates strong minority interaction effects on the probability of passing a course among students and the probability of receiving a grade of B or higher. All of these estimates imply large effects relative to the minority base rates and the white-minority gaps in outcomes. Underrepresented minority students are 1.2-2.8 percentage points more likely to pass classes relative to a minority base of 83 percent percent, 2.0-2.9 percent less likely to drop out of classes relative to minority base of 29 percent, and 2.4-3.2 percentage points more likely to get a grade of B or higher relative to a minority base of 55 percent in classes with underrepresented instructors. Our evidence of interaction effects at the extensive margin, like remaining in a course, and at the intensive margin, like grades within a course, suggests that students are influenced in multiple ways from instructors' racial and ethnic composition. .

The minority gap in the probability of continuing a subject in the following quarter is significantly affected by the minority status of the instructor as well.[28] This is

[27] The inclusion of course-minority fixed effects also helps condition out for possible minority interactions from students having a comparative advantage in some subjects. Minority students may be better at some of the subjects that minority instructors tend to teach. The inclusion of course-minority fixed effects control for this possibility. Examining performance by subject directly, we find that minority students perform at a lower level than non-minority students in all subjects. We also estimated the minority-non-minority grade gap by the concentration of minority instructors in that subject and found no relationship (see Appendix Figure 1).

[28] We investigate this further by estimating three sets of regression specifications related to choosing college majors using the different sources of variation for identification discussed in Section 3.2. We examine the minority instructor effect on 1) the first course/s taken in a subject, 2) choosing to major in that subject and 3) taking any additional courses in that subject. We find evidence of positive effects of minority

an important outcome of interest because it cannot be directly manipulated by the instructor and is thus more consistent with students reacting to instructors through, for example, role model effects than through preferential grading (which we investigate in more detail in Section 5).

Estimates vary across columns somewhat more when we use the restricted sample of low-registration priority students, however, estimates for all outcomes in our preferred specification reported in column 8 indicate significant minority interactions at least at the 10 percent significance level (the only exception is that we lose statistical significance for grades although the point estimate is very similar to the full sample). The lack of sensitivity of estimates to the low-registration priority students provides further evidence that is consistent with the lack of racial sorting across course offerings noted above. We continue to report estimates from both samples throughout because of the trade-off between restricting the sample to lessen concerns about potential sorting and using the full sample to increase precision.

Table 4 shows these results to hold generally when estimating our model for detailed races rather than the aggregated minority group. While student fixed effects absorb the interaction for one of the student groups – in our case "whites" - the classroom fixed effects absorb the interaction for one of the instructor groups – again "whites". Thus, only 9 of the 16 race and ethnicity interactions are identified and all estimated interaction effects are relative to outcomes for white students with alternative instructor types. We present the P-value from F-tests for two hypotheses of major interest, namely for the presence of an own-race interaction and for the presence of any race interaction.

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instructors on minority students in majoring in that subject, taking any additional courses in that subject, and the total number of additional courses in that subject. These results confirm the course-level results for continuing a subject in the following quarter.

We find strong and robust evidence for own-race interactions. The positive interaction estimates are not overly sensitive to whether we use the full sample or limit the sample to low-registration priority students. We find positive interactions for all major racial groups with African-American students experiencing particularly large and robust relative gains from being taught by a same-race instructor. This is particularly noteworthy given that African-American students and instructors account for only 4 percent and 6 percent of the sample, respectively. We also find evidence that Hispanic student academic performance improves from assignment to Black instructors, rather than a White instructors (but not vice versa).

4.3 Robustness Checks and External Validity

Although there is robust evidence against differential sorting, the fixed effects control for most problems with selection, and limiting the sample to low-registration priority students restricts choice, we address remaining concerns that unobserved differences in student traits between minority and non-minority students vary across classes based on the minority-status of the instructor. We experiment with three specifications that further restrict the variation in instructor minority status within course-time and across classrooms. Results for various subsamples are shown in Table 5, with individual and class fixed effects included in all specifications.

First we consider a specification that drops observations for which courses in the same quarter are taught by both minority and non-minority instructors. Identification of minority student-instructor interactions therefore comes only from across quarter variation in instructor ethnicity or race. In the second of this set of regressions we further restrict the sample to exclude variation in instructor minority status within an academic year for a given course. In this case, students would have to postpone taking a course for an entire academic year to satisfy a potential racial preference in their instructor, which may be very difficult given the required sequencing of courses and two-year enrolment goals. The third specification focuses on a sample of students who failed to enrol in the course section of their first choice. We construct this sample from our unique administrative dataset that records all registration attempts by students and their order for ***any*** section within a course in which a student attempts to enrol. As noted above, we find that only 54.9 percent of low-registration priority students enrol in their first section choice.

We find a consistent pattern of significant minority interactions when using all students which are similar to the estimates from the main sample. When relying on the sample of students with a low registration priority our point estimates are consistent with the evidence presented above. Although the estimates are imprecise for this sample, their confidence intervals mostly contain the estimates from the full sample.

Further robustness exercises that are estimated on other subgroups by type of student and type of course are shown in Appendix Table 4. To summarize, first, we do not find evidence that the minority interactions are gender specific. Both male and female minority students perform relatively better with minority instructors compared to non-minority instructors. Second, results are robust to the exclusion of language courses or video-delivered courses.

Panel B of Appendix Table 4 displays results that explore whether our findings are driven by particular institutional features of community colleges relative to 4-year colleges. A first potential concern is students who have an "unstable" academic career and periodically enrol in courses at community college. We therefore limit our sample of students who are lowest on the registration priority list to those who enrol at the College for the first time. This yields point estimates that are nearly identical to those obtained from a sample of all low registration priority students, suggesting that our results are not driven by more senior students who are frequently leaving and returning to the college. The smaller sample size, however, leads to insignificance of our estimates.

A second concern regarding external validity arises due to the types of courses that are offered at community colleges. We therefore allow parameters to depend on whether courses are vocational or not and whether they can be transferred to the University of California and California State University systems. If anything we find that transferable courses and non-vocational courses have larger minority interaction effects for most outcomes.

4.4 Bounds analysis of interaction effects on grades

Table 6 displays lower and upper bounds of the minority interaction effects when using standardized grade outcomes as the dependent variable. We compute these bounds following the procedure described in Section 3.3 and interpret them as a robustness exercise. When using the full sample, estimates are bounded between 3.9 percent and 7.7 percent of a standard deviation in the course grade. The estimated lower and upper bounds are all statistically significant at conventional levels. When using the sample of low-priority students instead, the sample sizes decrease and the bounds widen. The bounds are 2.7 percent and 8.2 percent of a standard deviation in the course grade.

Standard errors increase by a factor 2, but the upper bounds are statistically significant. Taken together, these results provide further evidence of a robust and quite substantial minority interaction effect on grades, in addition to a substantial effect on the probability of dropping a class.

As argued above, we interpret our uncorrected estimates as representing a lower bound of minority interactions, since those who are at the margin of dropping a class and who are induced not to do so because they share the minority status with their instructor are more likely to be from the lower part of the student ability distribution. This monotonicity assumption can be tested by estimating a version of model (4) for the course dropout variable that allows for an interaction between the minority interaction and prior GPA. It is violated if the minority-interaction is stronger for those with a higher prior GPA. The estimated minority-interactions are -0.023 (s.e. 0.015) and -0.037 (s.e. 0.025) for the full sample and the sample of low registration priority students, respectively, while the corresponding triple-interactions with prior GPA are 0.0007 (s.e. 0.005) and 0.004 (s.e. 0.009) respectively. Since the minority effects are estimated to be negative, their positive interactions with prior GPA thus are in accordance with our hypothesis. However, these estimates are not significant, suggesting that differential dropout behavior does not depend systematically on a student's academic abilities.

4.5 Long-Term Outcomes

Do the social interactions we find at the course level aggregate to affect longer-term outcomes? We have shown that they do for subsequent course selection, but what about other educational outcomes that are more directly correlated with labour market outcomes such retention, degree completion, and transferring to 4-year colleges? Table 7 reports estimates from three main regression specifications for these aggregate outcomes that use different sources of identifying variation. We estimate relative effects for minority students on the share of minority instructors in the first term as described in section 3.4.

Examining longer term outcomes prevents the use of student or classroom fixed effects, but we can condition on students taking the same set of courses in their first term. We can also instrument instructor minority share in first term with deviations from trend in the share of minority instructors teaching for any given course, in any given term. Our earlier baseline results suggest conditioning on observable student background characteristics leads to similar estimates than when using student fixed effects. So perhaps our long-term estimated effects are reasonably unbiased.

The first outcome examined is an indicator variable for whether the student remains at the college over the next two quarters (a full academic year). The selection-on-observables model reported in Column 1 suggests that raising the share of minority instructors by one standard deviation (0.25) would increase the relative retention rate for minorities by about 2.5 percentage points (relative to a minority base rate of 62 percent). This change would close roughly one third of the white-minority gap in the retention rate. We obtain a similar estimate when adding fixed effects for the set of courses a student takes in the first term. When instrumenting instructor share with deviations from trend we also estimate a statistically significant effect on retention, though larger and less precise. The second outcome examined is whether a student obtains an associates or vocational degree. A one standard deviation increase in the minority instructor share leads to roughly a 1.5 percentage point higher relative probability of receiving a degree (relative to a minority base rate of 14 percent). Estimates from the IV model indicate larger, but less precisely estimated effects. The evidence for effects on transferring to a 4-year college, however, is mixed. We find a small and insignificant estimate in column one, but negative and positive estimates in the remaining two specifications. When estimating effects on transferring only to UC or Cal State campuses, we find smaller and less significant estimates. Overall, the race or ethnicity of an instructor appears to exert an important influence on the long-term outcomes of students in addition to short-term effects on grades and other course outcomes.[29]

4.6 Mechanisms

In this section, we further explore the candidate mechanisms driving the social interactions we estimate above. One key question is whether our estimated effects are due to students or instructors behaving differently. An obvious potential source of instructor discrimination is through grading. Several pieces of evidence, however, point against this explanation. First, we identified courses and departments that commonly use multiple choice, true/false, matching and performance tests, and/or math courses over of potentially more "subjective" essay-type tests, reports, presentations and class participation by conducting an extensive examination of course syllabi and web pages, course catalogues, and discussions with administrative staff and instructors. The use of multiple choice, true/false and matching type exams are prevalent at the college, which may be due in part to faculty having heavy teaching loads of 10-15 courses per academic

[29] These estimates are robust to alternative measures of the outcomes, having any minority instructor instead of the minority share of instructors, using all courses instead of first term courses, using the first observed term, and the included controls.

year. Appendix Table 5 shows that estimation of our model on this sample yields results that are very similar to those documented above. As these courses are graded more objectively, these results provide evidence in favour of interactions occurring from students reacting to instructors rather than the opposite.

Second, we have documented significant, robust, and sizable minority effects with respect to course dropout behaviour. The minority gap in this outcome decreases by 2 to 3 percentage points if the class is taught by a minority instructor. The decision to drop out of the class is made entirely by the student and must be made in the first three weeks of a term, well before final grades are assigned by instructors. Third, we also find evidence that race/ethnicity interactions affect longer term outcomes, such as taking subsequent courses in the same subject, major choice, retention, and degree receipt. Instructors have no direct effect through grading but possibly serve as role models or generate interest and continuing studies in a subject.[30] Fourth, when allowing minority effects to vary across three age groups we find an absence of interaction effects for older students (Appendix Table 5). This also goes against the theory of instructor-based discrimination on the logic that race or ethnicity based discrimination should not depend significantly on student age. Instead we find that our point estimates are the largest for students who are younger than the median aged student. These results are inconsistent with discrimination affecting all students of a certain race irrespective of age and are more in line with the idea that young students react more to race of the instructor.[31]

[30] Estimates of minority-interactions for long-term outcome are not sensitive to controlling for first-term grades suggesting that the indirect effect of obtaining a better grade in a course is not driving the positive estimates.

[31] Although we do not find evidence of preferential grading by type of instructor, another explanation for the interaction effects we estimate is that there exists a mechanical relationship whereby instructors' grading distributions are correlated with their minority status. Bar and Zussman (2012) find evidence from 'an elite research university' that grade distributions correlate with instructor voting behavior, which in turn

The above suggests that our interaction estimates are likely due to students behaving differently in response to instructor type rather than vice versa. Appendix Table 5 explores whether there are particular student groups who may be especially likely to gain from assignment to an instructor with the same minority status. Classifying students by whether they receive financial aid, whether they went to a private school, whether their high school had a high fraction of students who are eligible for a free-lunch program, or whether they grew up in a poor or rich neighbourhood, and estimating separate interactions for these groups, the results suggest that minority effects are fairly homogeneous. While standard errors for some of the interactions are fairly large, particularly those for small sub-populations, the point estimates are remarkably robust across subsamples. In most cases the minority effects are highly significant for the larger student group, and we cannot reject equality of the minority effects across more advantaged and disadvantaged students. Thus, minority students from all economic backgrounds appear to share the relative gains from assignment to a minority instructor.

An important consideration for understanding these relative gains is whether they occur due to minority students performing better with minority instructors or non-minority students performing worse. The former may arise from instructors serving as role models, inspiring underrepresented students. The latter may arise from group favouritism, where non-minorities, consciously or subconsciously, find it difficult to

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may correlate with race or ethnicity. Since minorities tend to score lower grades than non-minorities on average, they systematically benefit from instructors that tend to compress grades towards the upper tail. We tested for this possibility directly and found no evidence of grade distribution differences by minority instructor status. The average grade given by a minority instructor across all courses is 2.86 compared with 2.85 for non-minority instructors. The standard deviation of grades is 1.20 for minority instructors and 1.15 for non-minority instructors. The robustness of our main results to including course-minority fixed effects in regression specifications reported in Table 3 also suggest that this is not the case. Finally we also do not find that minority instructors are clustered in fields in which grades are higher or there is less variance in grades (see Appendix Figures 2 and 3, also see Appendix Table 7 for enrollments and instructor counts by department).

learn from a minority instructor. Our baseline results with classroom fixed effects have the advantage of conditioning on differences across classes and teaching styles, but they restrict our analysis to minority interactions that are only *relative* to non-minorities. However, to explore who benefits and who performs worse from different instructor types, we need to estimate student-instructor interactions separately for each student type, thus requiring the exclusion of instructor or classroom fixed effects. We also expand minority status into five groups: white, African-American, Hispanic, Asian, and Native American. Doing so allows us to estimate the full set of race/ethnic interactions to determine which kinds of social interactions matter the most. Appendix Table 6 reports each of these estimates of α_1 in equation (1) after adding student and course fixed effects as well as instructor characteristic controls. The coefficient is the effect from being matched to an instructor of different type to a student's own race/ethnicity relative to being matched to one of the same type.

Appendix Table 6 shows evidence that students perform better with instructors of the same race/ethnicity, both for minority or non-minority students. For example, white students are 3.8 percentage points less likely to drop a course with a white instructor compared to an African-American instructor, whereas African-American students are 4.6 percentage points less likely to drop with an African-American instructor compared to a white instructor. This finding that whites do relatively worse with black instructors while black students do relatively better with them suggests that the negative effects on whites are not driven by overall instructor quality differences (since we also control for course fixed effects). The results also highlight challenges in determining a preferred instructor allocation, since alternate allocations generate both student gains and losses.[32]

Interestingly, we find robust negative effects on performance of white students when being matched to non-white instructors for our other academic outcomes. The gains for African-American students of being matched to an African-American instructor are quite robust across samples and outcomes. We find less clear patterns for the other race- and ethnicity groups, including Hispanics. That some ethnic groups appear to respond less favourably when matched to instructors of their own type compared with the strong relative effects for white students deserves mention. Dee (2007) and Hoffmann and Oreopoulos (2009) observe similar patterns with respect to gender. In both studies, male students generally perform worse academically with female instructors while female students do as well with male or female instructors.

One explanation for this behaviour is that students from high status groups react more strongly to instructors from low-status groups, leading to a kind of self-fulfilling discrimination. Social psychologists often describe social interactions in terms of "in-group favouritism", where individuals that identify with each other tend to respond more positively because they perceive they have similar beliefs or culture, and respond negatively with others (Tajfel and Turner, 1979). Less attention has been given to the moderating role that social status plays - the greater one's social status, the greater one's tendency to display in-group favouritism (Sidanius et al., 1994). This may explain why white students benefit more from being with white instructors compared to Hispanic students with Hispanic instructors. The theory deserves more attention in future research.

[32] Graham, Imbens, and Ridder (2009) provide more discussion on the policy implications of multiple social interactions in the context of student classroom allocation by gender.

5. Conclusion

Using a unique administrative dataset that matches student course outcomes to instructor's race, we estimate for the first time the importance of racial interactions between instructors and students at the college level. The estimation of two-way fixed effect models for a very large number of both students and classrooms over five years addresses most concerns about potential biases in estimating racial interactions. Remaining concerns about the internal validity of our estimates are addressed by taking advantage of the severely restricted class enrolment options among low-registration priority students at a very popular and class-rationed community college, by restricting the variation in instructor minority status across classes within term or year, and by examining students who do not enrol in the course section of first choice based on registration attempt data. We find that minority students perform relatively better in classes when instructors are of the same race or ethnicity. Underrepresented minority students are 1.2-2.8 percentage points more likely to pass classes, 2.0-2.9 percent less likely to drop out of classes, and 2.4-3.2 percentage points more likely to get a grade of B or higher in classes with underrepresented instructors. All of these effects are large relative to the minority base rates and the white-minority gaps. They represent 20-50percent of the total gaps in classroom outcomes between white and underrepresented minority students at the college. We also find relative effects on grades of roughly 5 percent of a standard deviation from being assigned an instructor of similar minority status. Taken together with the large class dropout interaction effects, these impacts are notably larger than those found for gender interactions between students and instructors at all levels of schooling.

Using a compilation of data from several administrative sources we also examine minority instructor impacts on long-term outcomes. We find evidence that an instructor's race or ethnicity affects the likelihood of taking subsequent courses in the same subject and majoring in the subject. The share of minority instructors in the first quarter also affects a student's likelihood of retention and degree completion. The finding that our classroom interaction effects appear to translate into consequential impacts on education attainment is also noteworthy in suggesting race and ethnic influences may exist in other settings and cumulatively matter in other ways.

In examining courses that are more objectively graded such as those commonly relying on multiple choice tests and math courses, we find similar estimated effects on course outcomes. Taken together with the positive effects on long-term outcomes, negative effects on drop out behaviour, and similar effects for minority students of all ages, these results provide evidence that our positive estimates of minority interactions are likely due to students reacting to instructors rather than the other way around. Further evidence from the regression results suggests that these estimated positive minority interactions are due to both positive influences, with minority students performing better with minority instructors, and negative influences, with non-minority students doing worse with minority instructors.

Our results suggest that the academic achievement gap between white and underrepresented minority college students would decrease by hiring more underrepresented minority instructors. However, the desirability of this policy is complicated by the finding that students appear to react positively when matched to instructors of a similar race or ethnicity but negatively when not. Hiring more instructors of one type may also lead to greater student sorting and changes to classroom composition, which may also impact academic achievement. A more detailed understanding of heterogeneous effects from instructor assignment, therefore, is needed before drawing recommendations for improving overall outcomes. The topic is ripe for further research, especially in light of the recent debates and legislative changes over affirmative action.

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TABLE 1 - DESCRIPTIVE STATISTICS

PANEL A: Sample Characteristics, Student-Class Level

	Mean	Std. Dev.	*Total Number of Obs.*
Low Registration Priority Student	0.29	0.46	
Entering Student	0.10	0.30	*444,822*
Course has no variation in instructor underrepresented-minority status within quarter	0.61	0.24	
Course has no variation in instructor underrepresented-minority status within academic year	0.52	0.25	
Language Course	0.03	0.16	*446,225*
Video-Delivered Course	0.06	0.24	
Course transferable to UC or CSU Systems	0.70	0.46	
Vocational Course	0.26	0.44	*442,061*

PANEL B: Student Outcomes by Race/Ethnicity

			Underrepresented Minorities		
	White	*Asian*	*Hispanic*	*African American*	*Other Minority*
Dropped Course	0.24	0.26	0.28	0.30	0.28
Total Nr of Obs: 446,225	*(0.43)*	*(0.44)*	*(0.45)*	*(0.46)*	*(0.45)*
Passed Course	0.89	0.89	0.84	0.82	0.86
Total Nr of Obs: 320,835	*(0.31)*	*(0.32)*	*(0.37)*	*(0.39)*	*(0.35)*
Grade	2.90	2.91	2.58	2.51	2.71
Total Nr of Obs: 279,110	*(1.14)*	*(1.14)*	*(1.19)*	*(1.21)*	*(1.19)*
Good Grade (B or higher)	0.68	0.68	0.57	0.53	0.61
Total Nr of Obs: 279,110	*(0.47)*	*(0.47)*	*(0.50)*	*(0.50)*	*(0.49)*
Retention after First Term	0.70	0.75	0.61	0.63	0.69
Total Nr of Obs: 14,899	*(0.46)*	*(0.43)*	*(0.49)*	*(0.48)*	*(0.46)*
Obtain Degree	0.16	0.18	0.15	0.12	0.13
Total Nr of Obs: 15,342	*(0.37)*	*(0.38)*	*(0.36)*	*(0.33)*	*(0.34)*
Transfer to 4-Year College	0.48	0.50	0.29	0.35	0.40
Total Nr of Obs: 15,341	*(0.50)*	*(0.50)*	*(0.45)*	*(0.48)*	*(0.49)*

PANEL C: Student and Instructor Shares by Race/Ethnicity

	Students			**Instructors**		
	Mean	S.D.	*N*	Mean	S.D.	*N*
White	0.28	0.20		0.70	0.21	
Asian	0.51	0.25		0.14	0.12	
Hispanic	0.14	0.12	*31,961*	0.06	0.06	*942*
African-American	0.04	0.04		0.06	0.05	
Other Minority	0.03	0.03		0.04	0.03	

NOTES: Students and instructors belong to the group of "Underrepresented Minorities" if their race/ethnicity is Hispanic, African-American, or Native American, Pacific Islander, or other non-white.

TABLE 2 - SORTING REGRESSIONS

	OUTCOME			
	Student Age	***Student Gender***	***Cumulated Courses Prior to Enrolment***	***GPA Prior to Enrolment***
All Students	0.046	0.014	0.077	0.017
	(0.112)	*(0.011)*	*(0.126)*	*(0.020)*
All Low Registration Priority Students	0.083	0.013	-0.073	0.026
	(0.174)	*(0.017)*	*(0.101)*	*(0.042)*
Entering Students (==> Low Registration Priority)	0.037	-0.012	-0.070	-0.003
	(0.233)	*(0.034)*	*(0.081)*	*(0.106)*
Continuing Students, Low Registration Priority	-0.050	0.024	-0.024	0.062
	(0.214)	*(0.026)*	*(0.076)*	*(0.073)*
Continuing Students, Not Low Registration Priority	0.011	0.012	0.034	0.013
	(0.118)	*(0.013)*	*(0.122)*	*(0.021)*
FIXED EFFECTS (BY UNDERREPRESENTED MINORITY STATUS)				
Course-Year-Quarter		**Yes**		

NOTES: This table displays results from regressions of the minority-specific average student outcomes in a classroom on an indicator equal to one if the average is associated with minority students, an indicator if the class is taught by a minority instructor, the interaction between these two variables, and a set of fixed effects. We only report the coefficient on the interaction term, to be interpreted as the extent to which minority students sort into classrooms taught by minority instructors. Each cell is associated with a different regression. Students and instructors belong to the group of "Underrepresented Minorities" if their race/ethnicity is Hispanic, African-American, or Native American, Pacific Islander, or other non-white. Rows are defined by the subsample of students we consider. Outcomes used in the regressions vary across columns. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by course-term-minority.

TABLE 3 - ESTIMATED ROLE OF INSTRUCTOR MINORITY STATUS FOR STUDENT OUTCOMES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: STUDENT DROPPED COURSE								
Number of Observations:	***446,225***							
All Students	-0.007	-0.019 **	-0.022 **	-0.014	-0.020 ***	-0.015 **	-0.015 **	-0.020 ***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)
All Low Registration Priority Students	-0.013	-0.024 **	-0.033 **	-0.024 *	-0.024 **	-0.025 **	-0.022 **	-0.029 ***
	(0.014)	(0.013)	(0.014)	(0.013)	(0.011)	(0.012)	(0.010)	(0.011)
OUTCOME: STUDENT PASSED COURSE, CONDITIONAL ON FINISHING THE COURSE								
Number of Observations:	***320,835***							
All Students	0.006	0.001	0.001	0.016 *	0.013 *	0.005	0.004	0.012
	(0.011)	(0.009)	(0.010)	(0.010)	(0.008)	(0.008)	(0.009)	(0.008)
All Low Registration Priority Students	0.025 *	0.032 **	0.040 ***	0.051 ***	0.042 ***	0.014	0.019	0.028 *
	(0.015)	(0.013)	(0.015)	(0.017)	(0.015)	(0.015)	(0.012)	(0.017)
OUTCOME: STANDARDIZED STUDENT COURSE GRADE, CONDITIONAL ON FINISHING THE COURSE								
Number of Observations:	***278,857***							
All Students	0.047	-0.020	0.000	0.078 ***	0.056 **	0.026	0.033	0.054 ***
	(0.033)	(0.026)	(0.028)	(0.029)	(0.023)	(0.024)	(0.025)	(0.022)
All Low Registration Priority Students	0.085 *	0.035	0.039	0.119 ***	0.068 *	0.014	0.033	0.050
	(0.045)	(0.038)	(0.043)	(0.043)	(0.037)	(0.039)	(0.034)	(0.040)
OUTCOME: GOOD GRADE (B OR HIGHER), CONDITIONAL ON FINISHING THE COURSE								
Number of Observations:	***279,110***							
All Students	0.011	-0.007	-0.001	0.027	0.023 **	0.014	0.012	0.024 ***
	(0.019)	(0.011)	(0.011)	(0.017)	(0.010)	(0.010)	(0.010)	(0.010)
All Low Registration Priority Students	0.011	-0.001	-0.004	0.047 **	0.029 *	0.003	0.007	0.032 *
	(0.023)	(0.017)	(0.020)	(0.023)	(0.017)	(0.017)	(0.014)	(0.019)
OUTCOME: STUDENT ENROLS IN A SAME-SUBJECT COURSE IN THE SUBSEQUENT TERM								
Number of Observations:	***217,950***							
All Students	0.028	0.021 ***	0.016 **	0.037 **	0.012 *	0.007	0.002	0.013 *
	(0.019)	(0.008)	(0.008)	(0.016)	(0.007)	(0.008)	(0.008)	(0.007)
All Low Registration Priority Students	0.019	0.039 ***	0.028	0.038 *	0.027 *	0.024	0.015 **	0.038 **
	(0.025)	(0.016)	(0.017)	(0.022)	(0.015)	(0.018)	(0.017)	(0.018)
FIXED EFFECTS:								
Year-Quarter-Minority	**Yes**	**Yes**	No	No	No	No	**Yes**	No
Course	No	No	No	No	**Yes**	No	No	No
Course-Minority	No	**Yes**	No	No	No	No	No	No
Course-Minority-Year-Quarter	No	No	**Yes**	No	No	No	No	No
Student	No	No	No	**Yes**	**Yes**	No	No	**Yes**
Instructor	No	No	No	No	No	No	**Yes**	No
Classroom	No	No	No	No	No	**Yes**	No	**Yes**
CONTROLS:								
Instructor Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	No	No	No
Student Controls	**Yes**	**Yes**	**Yes**	No	No	**Yes**	**Yes**	No

NOTES: This table displays results from our main outcome regressions. We report the coefficient of the interaction between student's and instructor's underrepresented minority status. Each cell is associated with a different regression. Students and instructors belong to the group of "Underrepresented Minorities" if their race/ethnicity is Hispanic, African-American, or Native American, Pacific Islander, or other non-white. Student controls include, gender, cumulated GPA and a 4th-order polynomial in age; instructor controls include gender, a part-time indicator and a 4th-order polynomial in age. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by instructor.

TABLE 4 - ESTIMATED ROLE OF INSTRUCTOR RACE/ETHNICITY FOR STUDENT OUTCOMES, USING A SAMPLE WITH FOUR RACE/ETHNICITY-GROUPS

	All Students			All Low Registration Priority Students		
	Instructor Race/Ethnicity			*Instructor Race/Ethnicity*		
	African-American	*Hispanic*	*Asian*	*African-American*	*Hispanic*	*Asian*
OUTCOME:STUDENT DROPPED COURSE						
Number of Observations:						
Student Race/Ethnicity						
African-American	-0.078 ***	-0.018	0.011	-0.083 ***	-0.018	0.092 ***
	(0.020)	(0.019)	(0.016)	(0.034)	(0.038)	(0.033)
Hispanic	-0.019 *	-0.025 **	0.022 **	-0.007	-0.042 ***	0.050 ***
	(0.011)	(0.013)	(0.011)	(0.024)	(0.017)	(0.018)
Asian	-0.016 **	-0.011	-0.014 *	0.008	-0.003	-0.003
	(0.009)	(0.010)	(0.008)	(0.018)	(0.018)	(0.015)
F-test: Own-Race/Ethnicity Effect (P-value)		***0.000***			***0.006***	
F-test: Race/Ethnicity-Effect (P-value)		***0.000***			***0.000***	
OUTCOME: STUDENT PASSED COURSE, CONDITIONAL ON FINISHING THE COURSE						
Number of Observations:						
African-American	0.067 ***	-0.013	-0.009	0.094 ***	0.038	-0.010
	(0.016)	(0.025)	(0.015)	(0.031)	(0.050)	(0.030)
Hispanic	0.020 *	0.009	-0.026 **	0.066 **	0.023	-0.008
	(0.012)	(0.017)	(0.011)	(0.029)	(0.030)	(0.020)
Asian	0.007	0.000	0.004	0.010	0.017	0.015
	(0.010)	(0.008)	(0.006)	(0.019)	(0.016)	(0.016)
F-test: Own-Race/Ethnicity Effect (P-value)		***0.000***			***0.015***	
F-test: Race/Ethnicity-Effect (P-value)		***0.001***			***0.113***	
OUTCOME: STANDARDIZED STUDENT COURSE GRADE, CONDITIONAL ON FINISHING THE COURSE						
Number of Observations:						
African-American	0.187 **	0.018	0.010	0.153	0.071	0.041
	(0.044)	(0.088)	(0.031)	(0.096)	(0.184)	(0.087)
Hispanic	0.068 **	0.097 *	-0.029	0.103 *	0.092	-0.044
	(0.029)	(0.058)	(0.023)	(0.062)	(0.113)	(0.063)
Asian	0.054	0.012	0.047 **	0.066	0.072	0.019
	(0.036)	(0.031)	(0.021)	(0.054)	(0.058)	(0.048)
F-test: Own-Race/Ethnicity Effect (P-value)		***0.000***			***0.339***	
F-test: Race/Ethnicity-Effect (P-value)		***0.000***			***0.619***	
OUTCOME: GOOD GRADE (B OR HIGHER), CONDITIONAL ON FINISHING THE COURSE						
Number of Observations:						
African-American	0.090 ***	0.025	0.007	0.129 ***	0.044	0.025
	(0.024)	(0.037)	(0.018)	(0.044)	(0.083)	(0.040)
Hispanic	0.029 *	0.039 *	0.001	0.063 *	0.013	-0.010
	(0.016)	(0.022)	(0.012)	(0.033)	(0.053)	(0.028)
Asian	0.009	0.006	0.028 ***	0.035	0.003	0.006
	(0.015)	(0.012)	(0.009)	(0.025)	(0.031)	(0.021)
F-test: Own-Race/Ethnicity Effect (P-value)		***0.000***			***0.031***	
F-test: Race/Ethnicity-Effect (P-value)		***0.000***			***0.248***	
OUTCOME: STUDENT ENROLS IN A SAME-SUBJECT COURSE IN THE SUBSEQUENT TERM						
Number of Observations:						
African-American	0.022	0.010	-0.013	0.077	0.042	-0.069
	(0.024)	(0.025)	(0.019)	(0.056)	(0.069)	(0.047)
Hispanic	0.011	0.001	-0.009	0.026	0.045	0.005
	(0.010)	(0.014)	(0.013)	(0.035)	(0.043)	(0.038)
Asian	0.005	-0.008	-0.003	0.036	-0.006	0.025
	(0.013)	(0.013)	(0.010)	(0.030)	(0.033)	(0.025)
F-test: Own-Race/Ethnicity Effect (P-value)		***0.809***			***0.288***	
F-test: Race/Ethnicity-Effect (P-value)		***0.938***			***0.435***	

NOTES: This table displays results from outcome regressions in which we allow for interactions between all observed student and instructor races/ethnicities. We only show results for our preferred specification, which includes student and classroom fixed effects. We report the full set of 9 identified interactions for each regression. Since we include student and instructor fixed effects, all interactions involving white students or instructors are unidentified. Same race/ethnicity interactions are shown in red along the diagonal. P-values for a F-test of the existence of same-race/ethnicity interactions and for the existence of any race/ethnicity-interactions are also listed. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by instructor.

TABLE 5 - ESTIMATED ROLE OF INSTRUCTOR MINORITY STATUS FOR STUDENT OUTCOMES: ROBUSTNESS

	ALL STUDENTS					*LOW REGISTRATION PRIORITY STUDENTS*				
	Dropped Course	**Passed Course**	**Grade (Standar-dized)**	**Good Grade (B or higher)**	**Takes Same-Subject Course Subsequently**	**Dropped Course**	**Passed Course**	**Grade (Standar-dized)**	**Good Grade (B or higher)**	**Takes Same-Subject Course Subsequently**
Course-Quarters without Variation in Instructor Underrepresented Minority Status										
Minority Interaction	-0.014	0.023 **	0.097 ***	0.045 ***	0.002	-0.010	0.041	0.073	0.042	0.085
	(0.012)	(0.010)	(0.038)	(0.014)	(0.020)	(0.029)	(0.034)	(0.121)	(0.047)	(0.069)
Course-Years without Variation in Instructor Underrepresented Minority Status										
Minority Interaction	-0.021	0.012	0.065	0.042 ***	-0.013	-0.007	0.059	0.089	0.067	-0.042
	(0.015)	(0.011)	(0.046)	(0.016)	(0.027)	(0.036)	(0.045)	(0.185)	(0.074)	(0.091)
Students who do not sit in the Section of their Choice										
Minority Interaction	-0.010	0.017 *	0.052 **	0.025 **	0.009	0.004	0.030	0.033	0.027	0.043
	(0.009)	(0.009)	(0.023)	(0.012)	(0.015)	(0.021)	(0.023)	(0.056)	(0.024)	(0.030)

NOTES: This table explores the heterogeneity of our results across different student groups and types of courses considered. We report the coefficient of the interaction between student's and instructor's underrepresented minority status - referred to as "Minority Interaction". We only report results for our preferred specification, which includes student and classroom fixed effects. Students and instructors belong to the group of "Underrepresented Minorities" if their race/ethnicity is Hispanic, African-American, or Native American, Pacific Islander, or other non-white. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by instructor.

TABLE 6 - UPPER AND LOWER BOUNDS FOR ESTIMATED ROLE OF INSTRUCTOR MINORITY STATUS FOR STUDENT GRADE

	TRUNCATION BY OVERALL DROPOUT BEHAVIOUR				TRUNCATION BY COURSE-SPECIFIC DROPOUT BEHAVIOUR			
	All Students		Low Reg-Priority Students		All Students		Low Reg-Priority Students	
Lower Bound	0.039	*	0.027		0.039	*	0.034	
	(0.022)		(0.041)		(0.024)		(0.041)	
Uncorrected Estimate	*0.054*	*****	*0.050*		*0.054*	*****	*0.050*	
	(0.022)		*(0.040)*		*(0.022)*		*(0.040)*	
Upper Bound	0.077	***	0.082	**	0.072	***	0.062	*
	(0.022)		(0.042)		(0.022)		(0.041)	
Student Controls	No				Yes			
Student FE	Yes				No			
Classroom FE	Yes				Yes			

NOTES: This table shows uncorrected and sample-selection corrected estimates for the minority interaction when grade is used as the outcome variable. Sample corrected estimates are non-parametric bounds as described in Lee (2009) and implemented in Hoffmann and Oreopoulos (2009). Lower (upper) bounds are computed under the assumption that minority students induced to stay in a class come from the upper (lower) tail of the outcome distribution . The fraction to be dropped come from first-stage dropout-regressions.The first two columns report results when the trimming procedure relies on estimates of the minority interaction in dropout regressions that use the full sample; the last two columns report results when the trimming procedure relies on estimates of the minority interaction in dropout regressions we run for each course separately; in the latter case we need to replace student fixed effects by student controls to achieve identification. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by instructor.

TABLE 7 - ESTIMATED ROLE OF INSTRUCTOR MINORITY STATUS FOR LONG-TERM OUTCOMES

	Main Model		Course FE Model		IV Model	
OUTCOME: RETENTION						
Number of Observations:	***14,899***					
Minority Interaction	0.092	***	0.103	**	0.878	***
	(0.033)		(0.044)		(0.218)	
OUTCOME: OBTAIN DEGREE						
Number of Observations:	***15,342***					
Minority Interaction	0.058	**	0.066	*	0.366	**
	(0.028)		(0.036)		(0.182)	
OUTCOME: TRANSFER TO 4-YEAR COLLEGE						
Number of Observations:	***15,341***					
Minority Interaction	-0.059		-0.129	***	0.422	**
	(0.036)		(0.046)		(0.234)	
OUTCOME: TRANSFER TO 4-YEAR COLLEGE (ONLY INCLUDE CAL STATE AND UC CAMPUSES)						
Number of Observations:	***15,341***					
Minority Interaction	-0.016		-0.086	**	0.258	
	(0.034)		(0.043)		(0.225)	

NOTES: This table displays results from long-term outcome regressions. We report the coefficient of the interaction between student's underrepresented minority status and instructor's underrepresented minority share. Only courses taken in the first term of a student's academic career at the college are included in the measurement of underrepresented minority instructor share. Each cell is associated with a different regression. We explore the sensitivity with respect to the regression specification: column 1 reports the main specification, column 2 reports estimates after including course set fixed effects for the initial set of courses taken by students in the term, and column 3 reports estimates in which the deviation from steady state minority instructor share for each department is used as an instrument for the minority instructor share. Controls included in all regressions are student's age, age squared, gender, financial aid receipt, educational goals at the time of application, free and reduced lunch rate of high school, private high school, year dummy for quarter of first term, number of courses taken in that quarter, instructor's full-time status, and instructor's age. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level.

APPENDIX TABLE 1 - SORTING REGRESSIONS WITH CLUSTERING BY INSTRUCTOR

	OUTCOME			
	Student Age	***Student Gender***	***Cumulated Courses Prior to Enrolment***	***GPA Prior to Enrolment***
All Students	0.046	0.014	0.077	0.017
	(0.102)	*(0.010)*	*(0.105)*	*(0.023)*
All Low Registration Priority Students	0.083	0.013	-0.073	0.026
	(0.143)	*(0.016)*	*(0.086)*	*(0.040)*
Entering Students (==> Low Registration Priority)	0.037	-0.012	-0.070	-0.003
	(0.169)	*(0.033)*	*(0.066)*	*(0.085)*
Continuing Students, Low Registration Priority	-0.050	0.024	-0.024	0.062
	(0.160)	*(0.022)*	*(0.068)*	*(0.056)*
Continuing Students, Not Low Registration Priority	0.011	0.012	0.034	0.013
	(0.111)	*(0.012)*	*(0.116)*	*(0.023)*
FIXED EFFECTS (BY UNDERREPRESENTED MINORITY STATUS)				
Course-Year-Quarter		**Yes**		

NOTES: This table displays results from regressions of the minority-specific average student outcomes in a classroom on an indicator equal to one if the average is associated with minority students, an indicator if the class is taught by a minority instructor, the interaction between these two variables, and a set of fixed effects. We only report the coefficient on the interaction term, to be interpreted as the extent to which minority students sort into classrooms taught by minority instructors. Each cell is associated with a different regression. Students and instructors belong to the group of "Underrepresented Minorities" if their race/ethnicity is Hispanic, African-American, or Native American, Pacific Islander, or other non-white. Rows are defined by the subsample of students we consider. Outcomes used in the regressions vary across columns. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by instructor.

APPENDIX TABLE 2 - ESTIMATED ROLE OF INSTRUCTOR MINORITY STATUS FOR STUDENT OUTCOMES WITH STANDARD ERRORS CLUSTERED BY CLASSROOM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: STUDENT DROPPED COURSE								
Number of Observations:	***446,225***							
All Students	-0.007	-0.019 ***	-0.022 ***	-0.014 ***	-0.020 ***	-0.015 ***	-0.015 ***	-0.020 ***
	(0.005)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
All Low Registration Priority Students	-0.013	-0.024 **	-0.033 ***	-0.024 ***	-0.024 ***	-0.025 **	-0.022 ***	-0.029 ***
	(0.010)	(0.011)	(0.012)	(0.010)	(0.009)	(0.011)	(0.009)	(0.011)
OUTCOME: STUDENT PASSED COURSE, CONDITIONAL ON FINISHING THE COURSE								
Number of Observations:	***320,835***							
All Students	0.006	0.001	0.001	0.016 ***	0.013 ***	0.005	0.004	0.012 ***
	(0.005)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
All Low Registration Priority Students	0.025 ***	0.032 ***	0.040 ***	0.051 ***	0.042 ***	0.014	0.019 **	0.028 **
	(0.010)	(0.011)	(0.013)	(0.011)	(0.010)	(0.011)	(0.009)	(0.012)
OUTCOME: STANDARDIZED STUDENT COURSE GRADE, CONDITIONAL ON FINISHING THE COURSE								
Number of Observations:	***278,857***							
All Students	0.047 ***	-0.020	0.000	0.078 ***	0.056 ***	0.026 **	0.033 ***	0.054 ***
	(0.015)	(0.018)	(0.019)	(0.015)	(0.014)	(0.014)	(0.014)	(0.013)
All Low Registration Priority Students	0.085 ***	0.035	0.039	0.119 ***	0.068 **	0.014	0.033	0.050
	(0.028)	(0.033)	(0.036)	(0.032)	(0.029)	(0.031)	(0.026)	(0.033)
OUTCOME: GOOD GRADE (B OR HIGHER), CONDITIONAL ON FINISHING THE COURSE								
Number of Observations:	***279,110***							
All Students	0.011	-0.007	-0.001	0.027 ***	0.023 ***	0.014 **	0.012 **	0.024 ***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
All Low Registration Priority Students	0.011	-0.001	-0.004	0.047 ***	0.029 **	0.003	0.007	0.032 **
	(0.014)	(0.015)	(0.016)	(0.015)	(0.013)	(0.014)	(0.012)	(0.016)
OUTCOME: STUDENT ENROLS IN A SAME-SUBJECT COURSE IN THE SUBSEQUENT TERM								
Number of Observations:	***217,950***							
All Students	0.028 ***	0.021 ***	0.016 **	0.037 ***	0.012 *	0.007	0.002	0.013 *
	(0.009)	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
All Low Registration Priority Students	0.019	0.039 ***	0.028 *	0.038 **	0.027 **	0.024 *	0.015	0.038 **
	(0.016)	(0.015)	(0.016)	(0.017)	(0.014)	(0.015)	(0.012)	(0.018)
FIXED EFFECTS:								
Year-Quarter-Minority	**Yes**	**Yes**	No	No	No	No	**Yes**	No
Course	No	No	No	No	**Yes**	No	No	No
Course-Minority	No	**Yes**	No	No	No	No	No	No
Course-Minority-Year-Quarter	No	No	**Yes**	No	No	No	No	No
Student	No	No	No	**Yes**	**Yes**	No	No	**Yes**
Instructor	No	No	No	No	No	No	**Yes**	No
Classroom	No	No	No	No	No	**Yes**	No	**Yes**
CONTROLS:								
Instructor Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	No	No	No
Student Controls	**Yes**	**Yes**	**Yes**	No	No	**Yes**	**Yes**	No

NOTES: This table displays results from our main outcome regressions. We report the coefficient of the interaction between student's and instructor's underrepresented minority status. Each cell is associated with a different regression. Students and instructors belong to the group of "Underrepresented Minorities" if their race/ethnicity is Hispanic, African-American, or Native American, Pacific Islander, or other non-white. Student controls include, gender, cumulated GPA and a 4th-order polynomial in age; instructor controls include gender, a part-time indicator and a 4th-order polynomial in age. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by classroom.

APPENDIX TABLE 3 - ESTIMATED ROLE OF INSTRUCTOR MINORITY STATUS FOR STUDENT OUTCOMES, ALTERNATIVE DEFINITION OF MINORITY-INTERACTION

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: STUDENT DROPPED COURSE								
Number of Observations:	***446,225***							
All Students	-0.011	-0.020	-0.021	-0.014	-0.026 **	-0.028 ***	-0.027 ***	-0.033 ***
	(0.015)	*(0.014)*	*(0.015)*	*(0.014)*	*(0.012)*	*(0.009)*	*(0.009)*	*(0.009)*
All Low Registration Priority Students	-0.029 *	-0.038 ***	-0.033 **	-0.024	-0.037 ***	-0.057 ***	-0.050 ***	-0.057 ***
	(0.015)	*(0.015)*	*(0.015)*	*(0.016)*	*(0.014)*	*(0.014)*	*(0.011)*	*(0.014)*
OUTCOME: STUDENT PASSED COURSE, CONDITIONAL ON FINISHING THE COURSE								
Number of Observations:	***320,835***							
All Students	0.029 **	0.004	0.006	0.038 ***	0.021 *	0.013	0.015	0.021 **
	(0.015)	*(0.013)*	*(0.013)*	*(0.015)*	*(0.013)*	*(0.010)*	*(0.010)*	(0.011)
All Low Registration Priority Students	0.033 *	0.012	0.017	0.062 **	0.039 **	0.004	0.015	0.026
	(0.017)	*(0.015)*	*(0.017)*	*(0.019)*	*(0.018)*	*(0.017)*	*(0.015)*	*(0.019)*
OUTCOME: STANDARDIZED STUDENT COURSE GRADE, CONDITIONAL ON FINISHING THE COURSE								
Number of Observations:	***278,857***							
All Students	0.075 *	0.044	0.074 *	0.108 ***	0.106 ***	0.064 **	0.083 ***	0.091 ***
	(0.043)	*(0.040)*	*(0.039)*	*(0.042)*	*(0.039)*	*(0.032)*	*(0.030)*	*(0.033)*
All Low Registration Priority Students	0.072	0.033	0.048	0.107 **	0.076	0.008	0.042	0.034
	(0.055)	*(0.052)*	*(0.054)*	*(0.055)*	*(0.058)*	*(0.059)*	*(0.051)*	*(0.063)*
OUTCOME: GOOD GRADE (B OR HIGHER), CONDITIONAL ON FINISHING THE COURSE								
Number of Observations:	***279,110***							
All Students	0.048 **	0.006	0.016	0.072 ***	0.042 ***	0.030 **	0.031 ***	0.042 ***
	(0.025)	*(0.015)*	*(0.015)*	*(0.024)*	*(0.015)*	*(0.013)*	*(0.012)*	*(0.013)*
All Low Registration Priority Students	0.028	-0.022	-0.017	0.072 **	0.025	-0.001	0.002	0.024
	(0.031)	*(0.022)*	*(0.023)*	*(0.032)*	*(0.026)*	*(0.025)*	*(0.021)*	*(0.029)*
OUTCOME: STUDENT ENROLS IN A SAME-SUBJECT COURSE IN THE SUBSEQUENT TERM								
Number of Observations:	***217,950***							
All Students	0.045	0.019 **	0.010	0.047 *	0.013	-0.003	-0.010	0.009
	(0.030)	*(0.010)*	*(0.009)*	*(0.027)*	*(0.009)*	*(0.011)*	*(0.012)*	*(0.010)*
All Low Registration Priority Students	0.019	0.024	0.010	0.026	0.020	0.004	-0.007	0.054 **
	(0.033)	*(0.019)*	*(0.020)*	*(0.033)*	*(0.018)*	*(0.025)*	*(0.018)*	*(0.026)*
FIXED EFFECTS:								
Year-Quarter-Minority	**Yes**	**Yes**	No	No	No	No	**Yes**	No
Course	No	No	No	No	**Yes**	No	No	No
Course-Minority	No	**Yes**	No	No	No	No	No	No
Course-Minority-Year-Quarter	No	No	**Yes**	No	No	No	No	No
Student	No	No	No	**Yes**	**Yes**	No	No	**Yes**
Instructor	No	No	No	No	No	No	**Yes**	No
Classroom	No	No	No	No	No	**Yes**	No	**Yes**
CONTROLS:								
Instructor Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	No	No	No
Student Controls	**Yes**	**Yes**	**Yes**	No	No	**Yes**	**Yes**	No

NOTES: This table displays results from our main outcome regressions when using an alternative definition of the student-instructor interaction. In particular, the interaction variable is equal to one only if the student and instructor have the same racial/ethnic background ***in addition to*** belonging to an underrepresented minority group. We only report the coefficient for this variable. Each cell is associated with a different regression. Students and instructors belong to the group of "Underrepresented Minorities" if their race/ethnicity is Hispanic, African-American, Native American, Pacific Islander, or other non-white. Student controls include, gender, cumulated GPA and a 4th-order polynomial in age; instructor controls include gender, a part-time indicator and a 4th-order polynomial in age. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by instructor.

APPENDIX TABLE 4 - ESTIMATED ROLE OF INSTRUCTOR MINORITY STATUS: ADDITIONAL ROBUSTNESS CHECKS AND EXTERNAL VALIDITY

	ALL STUDENTS					LOW REGISTRATION PRIORITY STUDENTS				
	Dropped Course	Passed Course	Grade (Standar-dized)	Good Grade (B or higher)	Takes Same-Subject Course Subsequently	Dropped Course	Passed Course	Grade (Standar-dized)	Good Grade (B or higher)	Takes Same-Subject Course Subsequently
PANEL A: ROBUSTNESS CHECKS										
Male vs. Female Students										
Minority Interaction**Male Students*	-0.021 ***	0.012	0.029	0.021	0.006	-0.019	0.038	0.021	0.031	0.020
	(0.008)	(0.010)	(0.030)	(0.014)	(0.010)	(0.016)	(0.024)	(0.053)	(0.026)	(0.027)
Minority Interaction**Female Students*	-0.019 **	0.012	0.073 ***	0.026 **	0.019 **	-0.037 ***	0.019	0.075	0.034	0.039 *
	(0.009)	(0.009)	(0.028)	(0.012)	(0.009)	(0.014)	(0.018)	(0.051)	(0.025)	(0.023)
Excluding Language Courses										
Minority Interaction	-0.018 ***	0.008	0.039 *	0.019 **	0.016 **	-0.027 **	0.022	0.021	0.025	0.030
	(0.007)	(0.008)	(0.021)	(0.009)	(0.007)	(0.012)	(0.018)	(0.034)	(0.017)	(0.019)
Excluding Video-Delivered Courses										
Minority Interaction	-0.015 **	0.012	0.053 **	0.025 ***	0.013 *	-0.024 **	0.030 *	0.056	0.033 *	0.030
	(0.007)	(0.008)	(0.022)	(0.010)	(0.007)	(0.012)	(0.018)	(0.041)	(0.020)	(0.019)
PANEL B: EXTERNAL VALIDITY										
Entering Students (==> Low Registration Priority)										
Minority Interaction	-	-	-	-		-0.025	0.032	0.048	0.033	0.024
						(0.029)	(0.028)	(0.097)	(0.050)	(0.053)
Vocational vs. Non-Vocational Courses										
Minority Interaction**NonVocational Course*	-0.025 ***	0.011	0.055 **	0.021 **	0.011	-0.034 ***	0.031	0.072	0.041 **	0.026
	(0.008)	(0.010)	(0.024)	(0.011)	(0.007)	(0.013)	(0.020)	(0.045)	(0.021)	(0.019)
Minority Interaction**Vocational Course*	0.000	0.016	0.052	0.034 *	0.002	0.010	0.011	-0.072	-0.019	0.104 **
	(0.010)	(0.010)	(0.055)	(0.019)	(0.018)	(0.023)	(0.031)	(0.083)	(0.036)	(0.053)
Courses that are Transferable to UC and CSU Systems										
Minority Interaction**NonTransferable Course*	-0.004	0.015	0.026	0.023	0.015	-0.017	0.038	0.057	0.046 *	0.050 *
	(0.010)	(0.011)	(0.043)	(0.018)	(0.011)	(0.020)	(0.028)	(0.054)	(0.024)	(0.030)
Minority Interaction**Transferable Course*	-0.030 ***	0.010	0.065 ***	0.024 **	0.012	-0.038 ***	0.021	0.048	0.027	0.031
	0.008	0.010	0.025	0.011	0.008	0.013	0.017	0.047	0.024	0.022

NOTES: This table explores the heterogeneity of our results across different student groups and types of courses considered. We report the coefficient of the interaction between student's and instructor's underrepresented minority status. We only report results for our preferred specification, which includes student and classroom fixed effects. Students and instructors belong to the group of "Underrepresented Minorities" if their race/ethnicity is Hispanic, African-American, or Native American, Pacific Islander, or other non-white. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by instructor.

APPENDIX TABLE 5 - ESTIMATED ROLE OF INSTRUCTOR MINORITY STATUS AND STUDENT'S SOCIO-ECONOMIC BACKGROUND

	ALL STUDENTS					*LOW REGISTRATION PRIORITY STUDENTS*				
	Dropped Course	**Passed Course**	**Grade (Standar-dized)**	**Good Grade (B or higher)**	**Takes Same-Subject Course Subsequently**	**Dropped Course**	**Passed Course**	**Grade (Standar-dized)**	**Good Grade (B or higher)**	**Takes Same-Subject Course Subsequently**
Objectively Graded Courses Only										
Minority Interaction	-0.019 **	0.013	0.030 *	0.019 **	0.012	-0.011	0.027	0.027	0.040 **	0.044 **
	(0.009)	(0.010)	(0.018)	(0.009)	(0.008)	(0.015)	(0.019)	(0.039)	(0.019)	(0.023)
Different Age Groups of Students										
Minority Interaction****Student younger than 21.5 years***	-0.018 **	0.006	0.038	0.017	0.009	-0.029 **	0.039 *	0.078	0.043 *	0.029
	(0.008)	(0.012)	(0.028)	(0.013)	(0.010)	(0.013)	(0.023)	(0.053)	(0.023)	(0.022)
Minority Interaction****Student between 21.5 and 35 years***	-0.001	0.013	0.041	0.016	0.003	0.013	-0.022	-0.067	-0.025	0.009
	(0.009)	(0.013)	(0.032)	(0.016)	(0.015)	(0.018)	(0.026)	(0.078)	(0.035)	(0.038)
Minority Interaction****Student older than 35 years***	-0.016	-0.004	-0.048	-0.020	0.008	-0.032	-0.061	-0.125	-0.046	0.018
	(0.018)	(0.018)	(0.053)	(0.026)	(0.028)	(0.034)	(0.042)	(0.129)	(0.056)	(0.094)
Received Financial Aid										
Minority Interaction****Financial Aid***	-0.021 ***	0.011	0.053 *	0.025 *	0.017 *	-0.033 *	0.017	0.014	0.004	0.055 **
	(0.009)	(0.009)	(0.029)	(0.014)	(0.009)	(0.019)	(0.022)	(0.054)	(0.026)	(0.024)
Minority Interaction****No Financial Aid***	-0.019 ***	0.013	0.055 ***	0.022 **	0.009	-0.026 **	0.039 **	0.079 *	0.054 ***	0.023
	(0.008)	(0.008)	(0.022)	(0.010)	(0.010)	(0.012)	(0.018)	(0.045)	(0.021)	(0.024)
Graduated from Private School										
Minority Interaction****Private High School***	-0.016	0.016	0.036	-0.008	0.032	-0.078 *	0.030	0.035	0.049	0.075
	(0.025)	(0.023)	(0.067)	(0.033)	(0.037)	(0.044)	(0.058)	(0.169)	(0.091)	(0.082)
Minority Interaction*Non-***Private High School***	-0.027 ***	0.016 *	0.058 **	0.021 *	0.014 *	-0.038 **	0.038 *	0.052	0.035	0.038
	(0.008)	(0.009)	(0.025)	(0.012)	(0.008)	(0.016)	(0.023)	(0.055)	(0.026)	(0.026)
Fraction of Students in Free Lunch Programs at High School of Graduation										
Minority Interaction****few Free Lunch Students at HS***	-0.023 ***	0.016 *	0.062 ***	0.025 **	0.012	-0.032 **	0.036 *	0.057	0.035 *	0.038 *
	(0.007)	(0.009)	(0.023)	(0.011)	(0.008)	(0.013)	(0.019)	(0.047)	(0.022)	(0.022)
Minority Interaction****many Free Lunch Students at HS***	-0.034	0.024	0.118 *	0.060 *	0.062	0.029	0.009	-0.028	-0.042	0.123
	(0.029)	(0.025)	(0.076)	(0.036)	(0.043)	(0.065)	(0.075)	(0.191)	(0.100)	(0.115)
Average Income in High School Neighborhood										
Minority Interaction****poor neighborhood***	-0.027 **	0.013	0.073 *	0.020	0.027	-0.024	0.023	0.149	0.059	0.072
	(0.015)	(0.016)	(0.040)	(0.020)	(0.019)	(0.031)	(0.037)	(0.108)	(0.049)	(0.055)
Minority Interaction****avg neighborhood***	-0.027 ***	0.015	0.046 *	0.016	0.012	-0.044 ***	0.044 **	0.057	0.036	0.034
	(0.007)	(0.010)	(0.028)	(0.012)	(0.010)	(0.016)	(0.023)	(0.059)	(0.028)	(0.028)
Minority Interaction****rich neighborhood***	-0.033	0.019	0.087 *	0.028	0.019	-0.041	0.032	-0.039	-0.002	0.047
	(0.022)	(0.019)	(0.048)	(0.024)	(0.026)	(0.038)	(0.046)	(0.116)	(0.070)	(0.069)

NOTES: This table explores the heterogeneity of our results across different student groups. We report the coefficient on the interaction between student's and instructor's underrepresented minority status - referred to as "Minority Interaction". In cases where we allow minority effects to vary across student groups we report the interaction between the main variable of interest and indicator variables that are equal to one if a student belongs to a certain subgroup. "Objectively Graded Courses" include those courses and departments that commonly use multiple choice, true/false, and other objectively graded tests, and/or math courses. To find high schools with a high fraction of free lunch students we first compute the empirical distribution of the school-level fraction of pupils who receive free lunch. We then define high schools to have "many free lunch students" if its fraction of free lunch students exceeds the 90%-percentile of the corresponding empirical distribution. Likewise, a neighborhood is defined to be an “average income neighborhood” if its average income is contained in the 80% symmetric confidence interval of its distribution. We only report results for our preferred specification, which includes student and classroom fixed effects. Students and instructors belong to the group of "Underrepresented Minorities" if their race/ethnicity is Hispanic, African-American, or Native American, Pacific Islander, or other non-white. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by instructor.

APPENDIX TABLE 6 - ESTIMATED ROLE OF INSTRUCTOR RACE/ETHNICITY FOR STUDENT OUTCOMES, GROUP BY GROUP REGRESSIONS

	All Students: Instructor Race/Ethnicity (Comparison Group: Own Race/Ethnicity Instructors)					All Low Registration Priority Students: Instructor Race/Ethnicity (Comparison Group: Own Race/Ethnicity Instructors)				
	White	*African-American*	*Hispanic*	*Asian*	*Other Minority*	*White*	*African-American*	*Hispanic*	*Asian*	*Other Minority*
PANEL A: OUTCOME - STUDENT DROPPED COURSE										
White		0.038 **	0.026	0.027 *	-0.002		0.022	0.037	0.021	-0.015
		(0.017)	*(0.018)*	*(0.015)*	*(0.020)*		*(0.022)*	*(0.024)*	*(0.017)*	*(0.021)*
African-American	0.046 **		0.091 ***	0.116 **	-0.077	0.067 *		0.279 **	0.105	-0.264
	(0.023)		*(0.032)*	*(0.051)*	*(0.064)*	*(0.038)*		*(0.132)*	*(0.155)*	*(0.247)*
Hispanic	-0.012	0.039		0.038	-0.121 *	-0.031	0.014		0.076	-0.089
	(0.030)	*(0.031)*		*(0.046)*	*(0.065)*	*(0.027)*	*(0.064)*		*(0.079)*	*(0.139)*
Asian	-0.011	-0.008	-0.038		-0.060 **	-0.012	0.023	-0.025		-0.022
	(0.016)	*(0.029)*	*(0.036)*		*(0.029)*	*(0.017)*	*(0.039)*	*(0.048)*		*(0.042)*
Other Minority	0.096 ***	0.114	0.131 *	0.181 **		0.143 ***	0.406	0.617	0.202	
	(0.028)	*(0.103)*	*(0.077)*	*(0.078)*		*(0.049)*	*(0.925)*	*(0.526)*	*(0.328)*	
PANEL B: OUTCOME - STUDENT PASSED COURSE										
White		-0.008	-0.015	0.000	-0.041 *		-0.029	-0.021	-0.002	-0.048
		(0.018)	*(0.021)*	*(0.011)*	*(0.025)*		*(0.025)*	*(0.026)*	*(0.016)*	*(0.033)*
African-American	-0.060 **		-0.081	-0.067	-0.054	-0.097 **		-0.044	-0.029	-0.213
	(0.029)		*(0.065)*	*(0.053)*	*(0.109)*	*(0.046)*		*(0.220)*	*(0.211)*	*(0.151)*
Hispanic	0.031	0.032		-0.018	-0.033	-0.006	-0.022		-0.010	-0.226
	(0.032)	*(0.042)*		*(0.048)*	*(0.054)*	*(0.041)*	*(0.108)*		*(0.109)*	*(0.232)*
Asian	-0.005	0.016	-0.006		0.030	-0.002	-0.057	0.035		-0.036
	(0.011)	*(0.025)*	*(0.026)*		*(0.025)*	*(0.013)*	*(0.047)*	*(0.054)*		*(0.065)*
Other Minority	0.078 *	0.260 **	0.141	-0.033		0.076	-0.594	0.130	-1.082 **	
	(0.046)	*(0.134)*	*(0.135)*	*(0.086)*		*(0.090)*	*(0.640)*	*(0.704)*	*(0.540)*	
PANEL C: OUTCOME - COURSE GRADE										
White		-0.050	-0.029	-0.005	-0.125 *		-0.066	-0.049	0.017	-0.155 **
		(0.058)	*(0.094)*	*(0.039)*	*(0.073)*		*(0.081)*	*(0.088)*	*(0.049)*	*(0.067)*
African-American	-0.136 *		-0.179	-0.151	0.275	-0.194		1.572	-0.091	-
	(0.076)		*(0.175)*	*(0.137)*	*(0.305)*	*(0.155)*		*(1.388)*	*(0.485)*	
Hispanic	0.035	-0.023		-0.123	-0.048	0.084	-0.102		-0.321	-0.211
	(0.114)	*(0.128)*		*(0.140)*	*(0.228)*	*(0.095)*	*(0.281)*		*(0.251)*	*(0.594)*
Asian	-0.002	-0.014	0.073		0.039	0.025	-0.204	0.138		0.036
	(0.037)	*(0.092)*	*(0.113)*		*(0.085)*	*(0.045)*	*(0.145)*	*(0.204)*		*(0.185)*
Other Minority	0.153	0.154	0.401	-0.056		0.327	2.001	0.437	-1.296	
	(0.118)	*(0.341)*	*(0.464)*	*(0.260)*		*(0.255)*	*(1.854)*	*(2.288)*	*(0.926)*	
PANEL D: OUTCOME - GRADE OF AT LEAST B										
White		0.006	-0.025	-0.004	-0.041		-0.001	-0.009	0.002	-0.031
		(0.027)	*(0.034)*	*(0.018)*	*(0.026)*		*(0.035)*	*(0.039)*	*(0.022)*	*(0.036)*
African-American	-0.103 ***		-0.051	-0.055	0.240 *	-0.131 **		0.748	0.126	-
	(0.034)		*(0.073)*	*(0.066)*	*(0.145)*	*(0.063)*		*(0.962)*	*(0.254)*	
Hispanic	-0.014	0.015		0.021	-0.065	0.028	0.005		-0.009	0.084
	(0.039)	*(0.042)*		*(0.058)*	*(0.092)*	*(0.047)*	*(0.115)*		*(0.167)*	*(0.288)*
Asian	-0.008	-0.017	0.002		-0.011	0.009	-0.073	0.070		0.022
	(0.017)	*(0.047)*	*(0.043)*		*(0.033)*	*(0.020)*	*(0.078)*	*(0.074)*		*(0.089)*
Other Minority	0.026	-0.027	0.094	-0.011		0.052	0.660	0.247	-1.482 ***	
	(0.043)	*(0.180)*	*(0.202)*	*(0.127)*		*(0.101)*	*(1.432)*	*(1.381)*	*(0.364)*	
PANEL E: OUTCOME - STUDENT ENROLS IN A SAME-SUBJECT COURSE IN THE SUBSEQUENT TERM										
White		-0.008	0.011	-0.005	-0.002		-0.008	-0.018	-0.018	-0.023
		(0.009)	*(0.010)*	*(0.009)*	*(0.015)*		*(0.022)*	*(0.021)*	*(0.019)*	*(0.027)*
African-American	0.008		0.173 ***	0.023	-0.014	-0.006		0.336	-0.229	0.541
	(0.022)		*(0.061)*	*(0.077)*	*(0.178)*	*(0.051)*		*(0.279)*	*(0.270)*	*(0.368)*
Hispanic	-0.009	-0.073 **		-0.033	0.061	0.011	-0.032		-0.010	-0.139
	(0.014)	*(0.032)*		*(0.038)*	*(0.067)*	*(0.032)*	*(0.165)*		*(0.195)*	*(0.307)*
Asian	0.015 **	-0.011	0.012		-0.001	0.007	-0.014	0.002		-0.022
	(0.006)	*(0.017)*	*(0.013)*		*(0.020)*	*(0.014)*	*(0.049)*	*(0.069)*		*(0.090)*
Other Minority	0.033	-0.054	-0.06197	-0.115		0.019	-	-	-2.193	
	(0.034)	*(0.177)*	*(0.212)*	*(0.166)*		*(0.082)*			*(1.707)*	

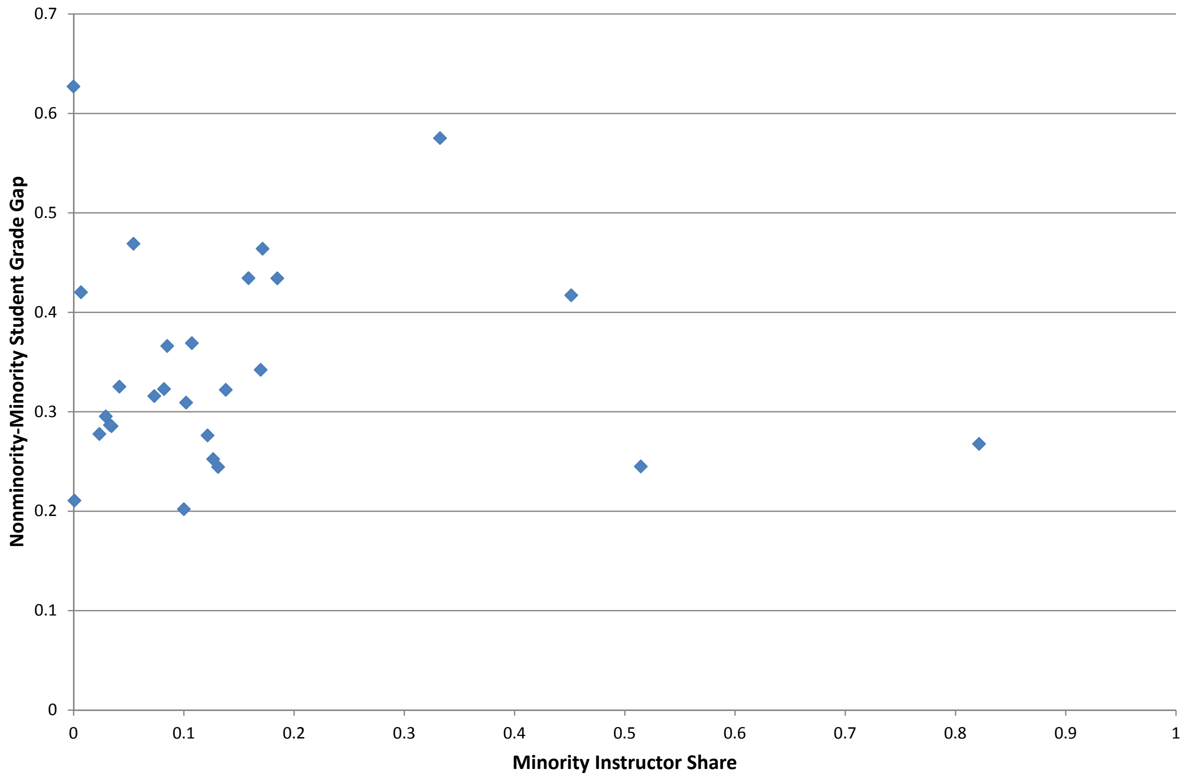
NOTES: In this table we investigate in detail if students lose or gain from being taught by an instructor of a different race/ethnicity. Each cell reports the estimated coefficient from a different regression that only uses one student group and two instructor groups. We only report results for our preferred specification, which includes student and classroom fixed effects. We compute the regression coefficients for a sample of all students and a sample of students with a low standing on class enrollment lists. *** Significant on 1%-level; ** Significant on 5%-level; * Significant on 10%-level. Standard errors are clustered by instructor.

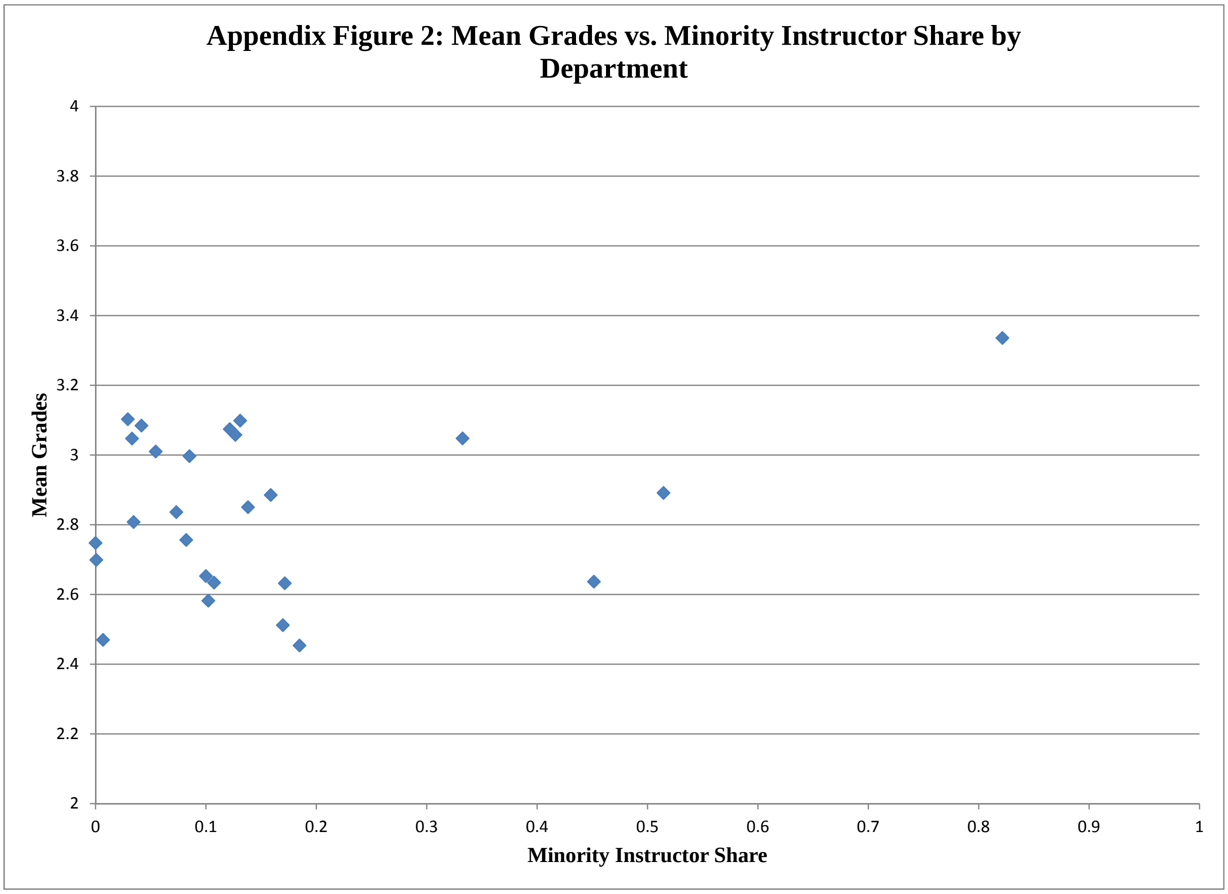
APPENDIX TABLE 7 - TOTAL ENROLLMENT AND INSTRUCTOR COUNTS BY DEPARTMENT

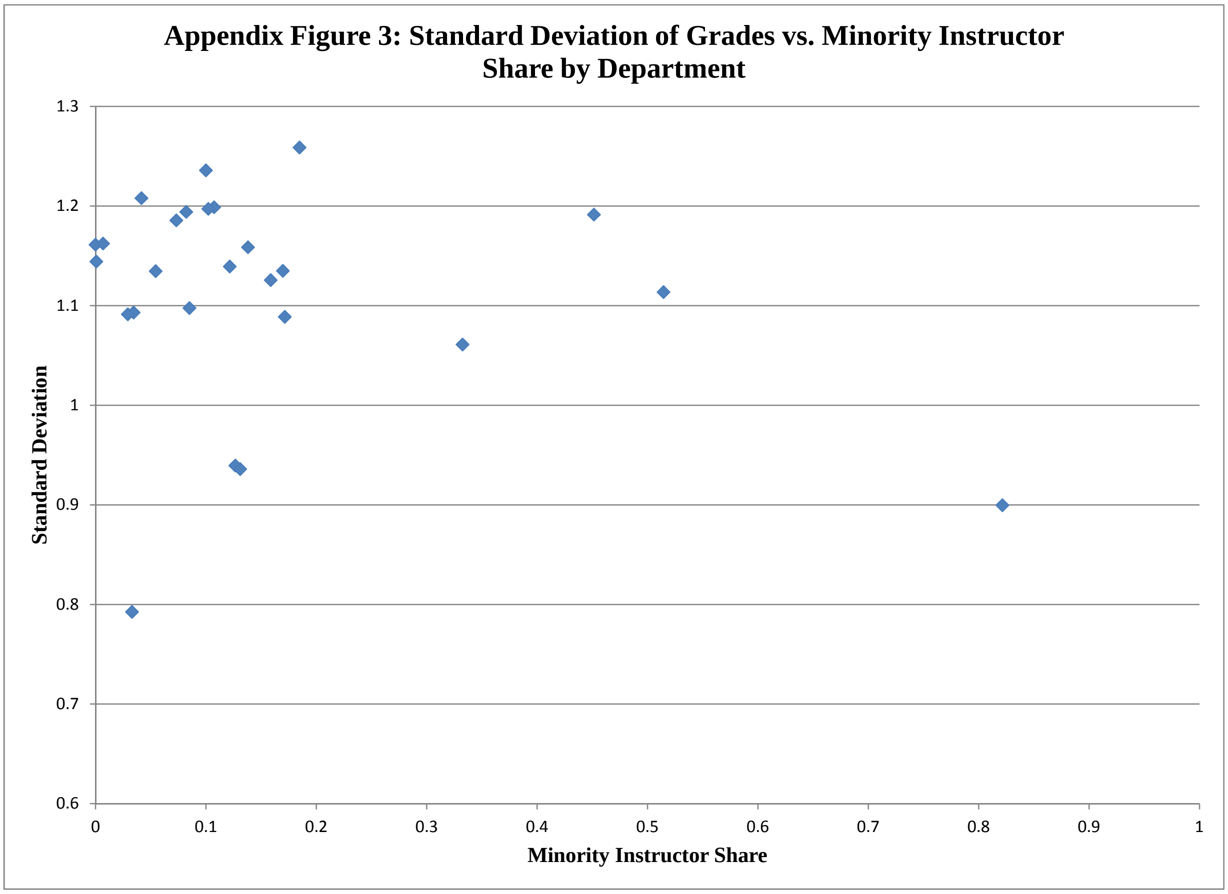
Department	***Enrollments***	***Number of Instructors***
Total	365,651	941
Accounting	16,187	37
Anthropology	9,941	15
Astronomy	7,960	3
Automotive Technology	5,339	13
Biology	14,896	34
Business	12,759	38
Child Development & Education	7,049	26
Computer Appl. & Ofc. Systems	7,077	15
Chemistry	7,460	21
Computer Information Systems	11,710	73
Economics	12,920	19
English/Writing	36,410	137
Film and Television Production	7,459	28
History	17,029	31
Human Development	6,471	15
Humanities	9,637	30
Mathematics	48,348	86
Nursing	6,059	32
Philosophy	7,871	22
Physics	5,203	14
Political Science	9,413	19
Psychology	13,132	36
Reading	9,701	22
Sociology	5,942	24
Speech/Communication	13,657	51

NOTES: Includes all enrollments in courses after drop period, but prior to withdrawal period. Only departments with at least 1 percent of total enrollment at college are reported.

Appendix Figure 1: Nonminority-Minority Student Mean Grade Gap vs. Minority Instructor Share by Department




Appendix Figure 2: Mean Grades vs. Minority Instructor Share by Department
Mean Grades
4
3.8
3.6
3.4
3.2
3
2.8
2.6
2.4
2.2
2
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Minority Instructor Share


Appendix Figure 3: Standard Deviation of Grades vs. Minority Instructor Share by Department
Standard Deviation
1.3
1.2
1.1
1
0.9
0.8
0.7
0.6
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Minority Instructor Share