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A Community College Instructor Like Me: Race and Ethnicity Interactions in the Classroom†

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Administrative data from a large and diverse community college are used to examine if underrepresented minority students benefit from taking courses with underrepresented minority instructors. To identify racial interactions, we estimate models that include both student and classroom fixed effects and focus on students with limited choice in courses. We find that the performance gap in terms of class dropout rates and grade performance between white and underrepresented minority students falls by 20 to 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. (*JEL* I23, J15, J44)

The achievement gap between historically underrepresented minority students and nonminority 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 nonminority students.[1] Fryer and Levitt (2006) and Fryer (2011) document that, for African Americans, achievement gaps 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]

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[1] See US 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 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

Fry (2002) and Arcidiacono, Aucejo, and Spenner (2011) find that similar gaps exist at postsecondary institutions. A major concern is that, in spite of substantial publicity and some affirmative action, the racial achievement gap has not shrunk over the last two decades, contrasting 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 groups.[4]

A common, though hotly debated, policy prescription for addressing these disparities 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 postsecondary level: only 9.6 percent of all full-time instructional faculty at US 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] The lack of minority instructors may impose severe limits on the availability of role models, increase the likelihood of "stereotype threats" and discrimination against minority students, and restrict 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 postsecondary education level. We test whether under represented 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] We estimate student-instructor minority interactions 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 in the San Francisco Bay Area. Our data contain comprehensive information on students' course-level academic outcomes, and long-term outcomes such as majors, retention, degree completion, and transfers to four-year colleges.

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 four-year colleges, they can be seen as a crucial part of the postsecondary educational system in the United States. In fact, in some states, including California, nearly one-half of all students attending a four-year college previously attended a community college.[7] With recent calls for major expansions in enrollments and provision of four-year transfer courses, one can expect that community colleges will gain further importance. Transfers from community colleges to the California State University (CSU, or Cal State) system, for example,

disparities (Rothstein and Wozny 2011), lower school quality (Fryer and Levitt 2004), differences in social norms (Austen-Smith and Fryer 2005), and for Hispanics whether English is spoken at home (Reardon and Galindo 2009).

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

[4] Such arguments are made in, e.g., Altonji and Blank (1999); Card (1999); and Jencks and Phillips (1998).

[5] See US Department of Education (2010).

[6] This is the common definition used for "underrepresented minority" in California public higher education.

[7] See US Department of Education (2010); CCCCO (2009); Sengupta and Jepsen (2006).

are projected to increase by 25 percent over the next decade (Wilson, Newell, and Fuller 2010).

It is well known that random assignment of students to classes does not occur at community colleges or four-year universities outside of the military postsecondary educational system.[8] 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 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 nonminority students of being assigned to a minority-instructor in the same class. The focus on estimation of a fixed effects model from panel data such as ours permits enormous flexibility in the types of specifications that can be estimated. 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 and that mitigate omitted variable biases that typically plague the empirical literature on student-instructor interactions.[9] Given the large number of fixed effects in our two-way-model 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.[10]

While our empirical model addresses many of the potential threats to internal validity, we cannot directly control for differential sorting that may arise if, for example, highly motivated minority students systematically sort into minority-taught classes while highly motivated nonminority students do not. We implement a test for this hypothesis using a rich set of observables that are likely to be highly correlated with unobserved student abilities, such as past academic performance, and do not find any evidence of differential sorting. Nevertheless, we exploit the institutional features of our community college to generate samples of students in which the incidence of endogenous sorting of students by instructor type is greatly minimized. We focus on students with limited class enrollment choices due to their low standing on registration priority lists. 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.

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 to 50 percent with a minority instructor and translate into longer-run impacts on taking subsequent courses in the same subject, 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

[8] Random assignment takes place at the US Air Force Academy, which provides undergraduate education for officers in the US Air Force (Carrell, Page, and West 2010).

[9] 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, section 001." Hence, a "class" or "classroom" is uniquely defined by course title, section, and term.

[10] See, for example, Abowd, Kramarz, and Margolis (1999) and Abowd, Creecy, and Kramarz (2002).

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 nonminority students performing 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), which use data from the elementary and eighth 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 postsecondary 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).[11] A recent study by Carrell, Page, and West (2010), which takes advantage of the random assignment of students to classrooms at the US Air Force Academy, also finds that female students perform better in math and science courses with female instructors. None of these previous studies, however, examine the impact of an instructor's race or ethnicity on student outcomes at the postsecondary education level, due to not being able to obtain race information on instructors and the lack of underrepresented minority faculty at more selective colleges. Even if a selective college existed with many minority faculty, the focus on a large, diverse community college such as ours is likely to be more representative of the average college experience for minority students in the United States. The lack of research on racial interactions at the college level might be an important omission in the literature, as the effects of minority faculty on minority students may be large because of the sizable 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 recently, in contrast to gender inequality.

I. Data

A. *Administrative Data and 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 enrollment 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.

[11] 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 2008; Carrington, Tymms, and Merrel 2008; Lahelma 2000; and Lavy and Schlosser 2011).

Our data contain information on course outcomes including grades, credits received, and course dropout behavior for every class offered by and every student enrolled at De Anza College from the fall quarter of 2002 to the spring quarter of 2007.[12] Each class is matched to corresponding instructor data, with information on demographic characteristics such as race, ethnicity, gender, and age. Classroom data is also matched to all students who initially enrolled, including information on race, ethnicity, gender, age, and various other characteristics. 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 four-year colleges—by linking National Student Clearinghouse data through summer 2012 to all of the students in our student-course level data.

An open enrollment policy—common to all community colleges in California—together with low tuition costs of \$17 per quarter unit (roughly \$850 per year in tuition and fees), mandated small class sizes (most below 50) and a desirable location, have created general excess demand for courses at the college. It has therefore established a strictly enforced registration priority system that 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 enrollment in special programs.[13] By analyzing detailed administrative data on all registration attempts and waitlists we find that students' registration priority indeed has a large impact on enrolling in preferred courses or timeslots. 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 enrollment, compared with approximately 74.5 percent for students with a higher registration priority. We also find higher probabilities of being placed on waitlists for first registration attempts among low registration priority students compared to students with higher registration priorities (7.2 percent compared with 3.4 percent).

B. *Sample Restrictions and Summary Statistics*

We exclude recreational courses, such as cooking, sports, and photography; orientation courses; and summer courses from the analysis. In the main sample, we also exclude courses that have an average enrollment per session of less than 15 students, courses in small academic departments, and students who are over 35 years old at the time they enter the sample. These restrictions account for roughly 10 percent of the sample.[14] The remaining sample consists of 446,225 student-class observations. Table 1 reports descriptive statistics. At the student-class level, 29 percent of observations are from students with low registration priority status and 61 percent of observations are from course-quarters that have no variation in underrepresented

[12] See Fairlie, Hoffman, and Oreopoulos (2014) for more details.

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

[14] See Fairlie, Hoffmann, and Oreopoulos (2014) for details.

Table 1—Descriptive Statistics

	Mean	SD	Observations
Panel A. Sample characteristics, student-class level			
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	0.49	
Course has no variation in instructor underrepresented-minority status within academic year	0.52	0.50	
Language course	0.03	0.16	
Video-delivered course	0.06	0.24	
Course transferrable to UC or CSU systems	0.70	0.46	446,225
Vocational course	0.26	0.44	442,061

			Underrepresented minorities		
	White	Asian	Hispanic	African American	Other minority
Panel B. Student outcomes by race/ethnicity					
Dropped course	0.24	0.26	0.28	0.30	0.28
Observations: 446,225	(0.43)	(0.44)	(0.45)	(0.46)	(0.45)
Passed course	0.89	0.89	0.84	0.82	0.86
Observations: 320,835	(0.31)	(0.32)	(0.37)	(0.39)	(0.35)
Grade	2.90	2.91	2.58	2.51	2.71
Observations: 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
Observations: 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
Observations: 14,899	(0.46)	(0.43)	(0.49)	(0.48)	(0.46)
Obtain degree	0.16	0.18	0.15	0.12	0.13
Observations: 15,342	(0.37)	(0.38)	(0.36)	(0.33)	(0.34)
Transfer to four-year college	0.48	0.50	0.29	0.35	0.40
Observations: 15,341	(0.50)	(0.50)	(0.45)	(0.48)	(0.49)

	Students			Instructors		
	Mean	SD	Obs.	Mean	SD	Obs.
Panel C. Student and instructor shares by race/ethnicity						
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.

minority status across sections. We use both of these subsamples to help address remaining course selection concerns.

In panel B of Table 1 we document important differences in academic outcomes across groups. White and Asian students have the highest average outcomes. Hispanics, African American, and Native American, Pacific Islander and other nonwhite 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). For all outcomes, these differences are large and statistically significant, documenting that the largest differences in academic outcomes take place along the minority-nonminority margin rather than along less aggregated measures of race and ethnicity. Aggregating up these statistics for the underrepresented minority group yields a dropout rate of 28 percent, an average grade-point average (GPA) of 2.6 (where 4.0 is equivalent to an A), and a course pass rate of 83.5 percent. Fifty-seven percent of grades are at least a B. African American, Latino, and other underrepresented minority students also have substantially worse long-term outcomes—lower retention rates, a lower fraction of degree completion, and a smaller share of students who transfer to a four-year college.

Panel C of Table 1 displays the racial and ethnic composition of the student and instructor body. Underrepresented minorities comprise 21 percent of the total student body, 14 percent of which are Hispanic, 4 percent are African American, and 3 percent are other minorities. The racial distribution of instructors differs from the student distribution. Seventy percent of instructors are white, whereas only 6 percent of instructors are Hispanic. The share of African American instructors, however, is slightly higher than the corresponding share of African American students. The lack of minority instructors at De Anza College does not differ substantially from all colleges in the nation. Ten percent of all college instructors are from underrepresented minority groups, compared with 16 percent at De Anza College (US Department of Education 2010).

II. Econometric Model and Estimation Strategy

Our main econometric model of student-course level outcomes y_{ijkst} is given by

$$y_{ijkst} = \alpha_0 + \alpha_1 \times min\_inst_j + \alpha_2 \times min\_stud_i + \alpha_3 \times min\_inst_j \times min\_stud_i + \mathbf{X}'_{ijkst}\boldsymbol{\beta} + u_{ijkst}, \tag{1}$$

where students are indexed by i, instructors by j, courses by k, sections by s, and term (i.e., quarter) by t.[15] The student and instructor-level variables min_stud_i and min_inst_j are indicator variables that are equal to one if student i and instructor j belong to an underrepresented minority group, respectively, and $\mathbf{X}_{ijkst}$ and u_{ijkst} are vectors of observable and unobservable variables. The parameter of interest is α_3 which measures the extent to which minority *gaps* in the outcome variables depend on whether the students are assigned to a minority or a nonminority instructor. It is greater than zero if minority students gain relative to nonminority students from being taught by a minority instructor, which is the student-instructor interaction of interest in our study. Including student fixed effects, γ_i, and classroom fixed effects, ϕ_{kst}, and dropping student- and class-level variables from equation (1) that are multicollinear with either of the fixed effects, we obtain our preferred empirical model:

$$y_{ic} = \alpha_3 \times min\_stud_i \times min\_inst_c + \gamma_i + \phi_c + u_{ic}, \tag{2}$$

[15] See Fairlie, Hoffmann, and Oreopoulos (2014) for a more detailed description.

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

The focus on the interaction term between students' and instructors' minority status allows us to identify student and classroom fixed effects, thereby overcoming many threats to internal validity. Importantly, our specification implicitly controls for instructor fixed effects and minority-specific course fixed effects. 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 implicitly standardize testing procedures *across* student groups that we are comparing, since within the same classroom students are taking exactly the same tests and are subjected 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 *absolute* 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 that may arise if, for example, highly motivated minority students sort systematically into minority-taught classes, while highly motivated nonminority students sort systematically into nonminority-taught classes. Note, however, that if there are minority gaps that persist across all classes, independent of instructor characteristics, they are implicitly controlled for through the inclusion of individual fixed effects and the estimation of what is essentially a difference-in-differences approach.

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 nonminority students. Since a classroom is associated with exactly one instructor minority status, these averages are the empirical counterparts of conditional expectations for the error terms. We can then test for differential sorting by estimating a difference-in-difference model:

$$(3) \quad \overline{X_{mc}} = \delta_1 \times min\_inst_c + \delta_2 \times I_m + \delta_3 \times min\_inst_c \times I_m + \nu_{mc},$$

where I_m is a dummy variable equal to 1 if $m = 1$ and 0 otherwise, and δ_3 is an empirical estimate of the difference-in-difference in conditional expectations of minority gaps in error terms in which x_{ic} proxies for the error term. 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 the error term. Given the richness of our data, we are able to use several variables, such as past academic performance, age and gender, to estimate "sorting regressions" such as equation (3). Even though we do not detect any evidence of differential sorting when implementing this test, as discussed in the next section, we estimate specifications in which the sample of students and courses is chosen to minimize the possibility of differential sorting across classes. In particular, we estimate equation (2) 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 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.

Estimation of the two-way fixed effects model of equation (2) with unbalanced panel data is computationally infeasible using ordinary least squares (OLS) with the more than 30,000 students and over 20,000 classrooms in our data. We thus rely on recent advances in the estimation of firm and worker fixed effects from administrative data.[16]

III. Results

A. *Evidence against Sorting*

With the inclusion of classroom and student fixed effects and the focus on the relative effect of assignment to a minority instructor, the primary threat to validity arises from the possibility of differential sorting. In particular, if classes where minority students tend to perform better relative to nonminority students are also classes with a minority instructor and if this effect is not due to the interaction itself but due to unobserved differences between the student groups, our estimates will be biased. We implement our test for differential sorting by estimating equation (3) for various background variables that are likely to be correlated with the unobserved ability term. Estimates of the interaction coefficient, δ_3, which measures the extent to which the minority gap in outcomes varies across classes taught by minority and nonminority instructors, are reported in Table 2. All standard errors are clustered at the course-term-minority level.[17] We use the following four background

[16] The seminal paper in this literature is Abowd, Kramarz, and Margolis (1999). Refinements have been developed by Abowd, Creecy, and Kramarz (2002) and Andrews et al. (2008). Cornelissen (2008) has written a Stata routine based on these algorithms. 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. See Fairlie, Hoffmann, and Oreopoulos (2014) for a more detailed discussion.

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

Table 2—Sorting Regressions

	Outcome			
	Student age	Female student	Cumulated courses prior to enrollment	GPA prior to enrollment
Average:	22.20	0.49	7.15	2.78
SD:	4.14	0.49	5.79	0.88
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, 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 at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

variables: student age, gender, the cumulated number of courses, and the cumulated GPA prior to enrollment. 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-nonminority gap of accumulated GPA prior to enrollment 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 subsamples, indicating that we cannot detect any systematic or robust sorting patterns in the data.[18] Most importantly, minority gaps in accumulated GPA prior to course enrollment—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 minority-taught classes compared with high ability

[18] 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.

nonminority students. We interpret this as strong evidence in favor of our working hypothesis of no differential sorting.

B. *Main Results*

Estimates of the minority interactions between students and instructors for our five course outcome variables using the full sample and a subsample of students who are low on the registration priority list are reported in Table 3. We explore the sensitivity of results with respect to the set of fixed effects; 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 (2), which includes both student and classroom fixed effects, are displayed in column 5 of Table 3. The other specifications reported in the table include minority-specific time fixed effects and a set of student and instructor controls (column 1), a specification with minority-specific course-time fixed effects (column 2), and specifications with student or classroom fixed effects (columns 3 and 4, respectively). Standard errors are clustered at the instructor-level.[19]

There are significant minority interaction effects on student dropout behavior 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 dropout behavior when taught by a minority instructor by 2 to 3 percentage points and in student grade 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.[20] 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 to 2.8 percentage points more likely to pass classes relative to a minority base of 83 percent, 2.0 to 2.9 percent less likely to drop out of classes relative to minority base of 29 percent, and 2.4 to 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)

[19] 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 online Appendix Table 2.

[20] 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 nonminority students in all subjects. We also estimated the minority-nonminority grade gap by the concentration of minority instructors in that subject and found no relationship (see online Appendix Figure 1).

Table 3—Estimated Role of Instructor Minority Status for Student Outcomes

	(1)	(2)	(3)	(4)	(5)
Student dropped course					
Observations	446,225				
All students	−0.007	−0.022**	−0.020 ***	−0.015**	−0.020***
	(0.010)	(0.011)	(0.007)	(0.007)	(0.007)
All low registration priority students	−0.013	−0.033**	−0.024**	−0.025**	−0.029***
	(0.014)	(0.014)	(0.011)	(0.012)	(0.011)
Student passed course, conditional on finishing the course					
Observations	320,835				
All students	0.006	0.001	0.013*	0.005	0.012
	(0.011)	(0.010)	(0.008)	(0.008)	(0.008)
All low registration priority students	0.025*	0.040***	0.042***	0.014	0.028*
	(0.015)	(0.015)	(0.015)	(0.015)	(0.017)
Standardized student course grade, conditional on finishing the course					
Observations	278,857				
All students	0.047	0.000	0.056**	0.026	0.054***
	(0.033)	(0.028)	(0.023)	(0.024)	(0.022)
All low registration priority students	0.085*	0.039	0.068*	0.014	0.050
	(0.045)	(0.043)	(0.037)	(0.039)	(0.040)
Good grade (B or higher), conditional on finishing the course					
Observations	279,110				
All students	0.011	−0.001	0.023**	0.014	0.024***
	(0.019)	(0.011)	(0.010)	(0.010)	(0.010)
All low registration priority students	0.011	−0.004	0.029*	0.003	0.032*
	(0.023)	(0.020)	(0.017)	(0.017)	(0.019)
Student enrolls in a same-subject course in the subsequent term					
Observations	217,950				
All students	0.028	0.016**	0.012*	0.007	0.013*
	(0.019)	(0.008)	(0.007)	(0.008)	(0.007)
All low registration priority students	0.019	0.028	0.027*	0.024	0.038**
	(0.025)	(0.017)	(0.015)	(0.018)	(0.018)
Fixed effects					
Year-quarter-minority	Yes	No	No	No	No
Course	No	No	Yes	No	No
Course-minority-year-quarter	No	Yes	No	No	No
Student	No	No	Yes	No	Yes
Classroom	No	No	No	Yes	Yes
Controls					
Instructor controls	Yes	Yes	Yes	No	No
Student controls	Yes	Yes	No	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, Native American, Pacific Islander, or other non-white. Student controls include, gender, cumulated GPA, and a fourth-order polynomial in age; instructor controls include gender, a part-time indicator, and a fourth-order polynomial in age. Standard errors are clustered by instructor.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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.[21] This is 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 IIID).

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 5 of Table 3 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.

Our specification using student-instructor interactions at the aggregated minority level implicitly assumes that minority students can be influenced by *any* minority instructor and by a similar amount. An alternative is to allow minority interactions to operate only when a student is matched with an instructor of the same detailed race or ethnicity. The underlying assumptions for such a specification are that: (i) there is no effect across minority types, and (ii) the performance gap from white and black students being assigned to a black instructor is the same as that for Hispanic and black students being assigned to a black instructor. We reproduce Table 3 using this alternative definition of the student-instructor interaction in online Appendix Table 3. If students were indeed only influenced by same-race or same-ethnicity instructors, we would expect the results in online Appendix Table 3 to be systematically stronger. This, however, is generally not the case, and in fact estimates of the interaction term in the two tables are quite similar.

To investigate further the level at which student-instructor interactions exist, we also report estimates from regressions that allow for separate interactions across all detailed racial and ethnic groups. 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 within a class. Results from this specification are shown in Table 4. In addition to the point estimates we present the p-value from F-tests for two hypotheses

[21] 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 below in Section IIIE. We examine the minority instructor effect on (i) the first course(s) taken in a subject, (ii) choosing to major in that subject, and (iii) taking any additional courses in that subject. We find evidence of positive effects of minority 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.

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
Student dropped course						
Observations		418,270			122,883	
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	
Student passed course, conditional on finishing the course						
Observations		300,503			89,031	
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	
Standardized student course grade, conditional on finishing the course						
Observations		260,466			70,871	
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	

(*Continued*)

of major interest, namely for the presence of an own-race interaction and for the presence of any race interaction. 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. Another important finding is that there is evidence of minority students benefiting from assignment to a minority instructor of a different race, e.g., Hispanic student academic performance improves from assignment to black instructors, rather than to white instructors.

Estimation of the econometric model for grade outcomes is possible only for the sample of students who complete the course. At the same time, as shown in

TABLE 4—ESTIMATED ROLE OF INSTRUCTOR RACE/ETHNICITY FOR STUDENT OUTCOMES, USING A SAMPLE WITH FOUR RACE/ETHNICITY GROUPS (*Continued*)

	All students			All low registration priority students		
	Instructor race/ethnicity			Instructor race/ethnicity		
	African American	Hispanic	Asian	African American	Hispanic	Asian
Good grade (B or higher), conditional on finishing the course						
Observations		260,707			70,925	
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	
Student enrolls in a same-subject course in the subsequent term						
Observations		203,951			59,417	
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 nine 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 bold. *p*-values for an *F*-test of the existence of same-race/ethnicity interactions and for the existence of any race/ethnicity interactions are also listed. Standard errors are clustered by instructor.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 3, the propensity to finish a course is affected by the variable of interest—the minority-status interactions between students and instructors within classrooms. This creates a classical sample selection problem that is difficult to correct using a Heckman-selection estimator since any variable affecting dropout behavior arguably also affects potential grades. Instead, we estimate nonparametric bounds that are based on worst-case selection scenarios, following Lee (2009).[22] This estimator can only be used for continuous outcome variables. We thus compute the bounds only for the grade variable. Online Appendix Table 4 reports estimates.

When using the full sample, estimates are bounded between 3.9 percent and 7.7 percent of a standard deviation in the course grade, and when using the sample of low priority students the bounds are 2.7 percent and 8.2 percent of a standard deviation. 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. We interpret our uncorrected estimates as representing a lower bound of minority interactions, since those who are at the

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

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. Fairlie, Hoffmann, and Oreopoulos (2014) provide some evidence for this hypothesis.

C. *Robustness Checks and External Validity*

In this section, we report results from several alternative specifications that provide additional robustness checks and explore issues around external validity. We experiment with three specifications that further restrict choice in instructor minority status and report estimates in panel A of Table 5. Estimates from our preferred model which includes student and classroom fixed effects are reported. First, we consider a specification that excludes observations for which courses in the same quarter are taught by both minority and nonminority instructors. Identification of minority student-instructor interactions therefore comes only from across quarter variation in instructor race. Second, 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 many courses and two-year enrollment goals. The third specification focuses on a sample of students who failed to enroll in the course section of their first choice. We construct this sample from our administrative records of all student registration attempts to *any* section within a course. As noted earlier, we find that only 54.9 percent of low registration priority students enroll in their first section choice.

For all of these specifications we find a consistent pattern of significant minority interactions which are similar to the estimates from the main sample when using all students. 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 online Appendix Table 5. To summarize, first, we do not find systematic evidence that the minority interactions are gender specific. Both male and female minority students perform relatively better with minority instructors compared to nonminority instructors. Second, results are robust to the exclusion of language courses or video-delivered courses.

Panel B of online Appendix Table 5 investigates the external validity of our estimates. It displays results that explore whether our findings are driven by particular institutional features of community colleges relative to four-year colleges. A first potential concern is students who have an "unstable" academic career and periodically enroll in courses at community college. We therefore limit our sample of students who are lowest on the registration priority list to those who enroll 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.

Table 5—Estimated Role of Instructor Minority Status for Student Outcomes: Robustness and Mechanisms

	Dropped course	Passed course	Grade (standardized)	Good grade (B or higher)	Takes same-subject course subsequently
Panel A. Robustness			All students		
Course-quarters without variation in instructor underrepresented minority status					
Minority interaction	−0.014	0.023**	0.097***	0.045***	0.002
	(0.012)	(0.010)	(0.038)	(0.014)	(0.020)
Course-years without variation in instructor underrepresented minority status					
Minority interaction	−0.021	0.012	0.065	0.042***	−0.013
	(0.015)	(0.011)	(0.046)	(0.016)	(0.027)
Students who do not sit in the section of their choice					
Minority interaction	−0.010	0.017*	0.052**	0.025**	0.009
	(0.009)	(0.009)	(0.023)	(0.012)	(0.015)
			Low registration priority students		
Course-quarters without variation in instructor underrepresented minority status					
Minority interaction	−0.010	0.041	0.073	0.042	0.085
	(0.029)	(0.034)	(0.121)	(0.047)	(0.069)
Course-years without variation in instructor underrepresented minority status					
Minority interaction	−0.007	0.059	0.089	0.067	−0.042
	(0.036)	(0.045)	(0.185)	(0.074)	(0.091)
Students who do not sit in the section of their choice					
Minority interaction	0.004	0.030	0.033	0.027	0.043
	(0.021)	(0.023)	(0.056)	(0.024)	(0.030)
Panel B. Mechanisms			All students		
Objectively graded courses only					
Minority interaction	−0.019**	0.013	0.030*	0.019**	0.012
	(0.009)	(0.010)	(0.018)	(0.009)	(0.008)
Different age groups of students					
Minority interaction	−0.018**	0.006	0.038	0.017	0.009
× student younger than 21.5 years	(0.008)	(0.012)	(0.028)	(0.013)	(0.010)
Minority interaction	−0.001	0.013	0.041	0.016	0.003
× student between 21.5 and 35 years	(0.009)	(0.013)	(0.032)	(0.016)	(0.015)
Minority interaction	−0.016	−0.004	−0.048	−0.020	0.008
× student older than 35 years	(0.018)	(0.018)	(0.053)	(0.026)	(0.028)
			Low registration priority students		
Objectively graded courses only					
Minority interaction	−0.011	0.027	0.027	0.040**	0.044**
	(0.015)	(0.019)	(0.039)	(0.019)	(0.023)
Different age groups of students					
Minority interaction	−0.029**	0.039*	0.078	0.043*	0.029
× student younger than 21.5 years	(0.013)	(0.023)	(0.053)	(0.023)	(0.022)
Minority interaction	0.013	−0.022	−0.067	−0.025	0.009
× student between 21.5 and 35 years	(0.018)	(0.026)	(0.078)	(0.035)	(0.038)
Minority interaction	−0.032	−0.061	−0.125	−0.046	0.018
× student older than 35 years	(0.034)	(0.042)	(0.129)	(0.056)	(0.094)

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." "Objectively graded courses" include those courses and departments that commonly use multiple choice, true/false, and other objectively graded tests, and/or math courses. 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, Native American, Pacific Islander, or other non-white.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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 transferrable courses and nonvocational courses have larger minority interaction effects for most outcomes.

D. *Mechanisms*

We now explore the candidate mechanisms driving the social interactions estimated 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 potentially more "subjective" essay-type tests, reports, presentations, and class participation by conducting an extensive examination of course syllabi and web pages, course catalogs, 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 year. Panel B of Table 5 shows that estimation of our model on this sample yields results that are very similar to the main results. Because these courses are graded more objectively, the results provide evidence in favor 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 behavior. 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 by the student and must be made in the first three weeks of a term, well before final grades are assigned by instructors. Third, as shown above and in the next section, 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.[23] Fourth, when allowing minority effects to vary across three age groups we find a robust absence of interaction effects for older students, as shown in panel B of Table 5. Instead, we find that our point estimates are the largest for students who are younger than the median-aged student. 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.[24]

[23] 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.

[24] 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 may correlate with race or ethnicity. Since minorities tend to score lower grades than nonminorities 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

These results together suggest that our interaction estimates are likely due to students behaving differently in response to instructor type rather than vice versa. Online Appendix Table 6 explores whether there are particular student groups who may be especially likely to gain from assignment to an instructor with the same minority status. Estimating separate interactions for students by whether they receive financial aid, they went to a private school, their high school had a high fraction of students who were eligible for free-lunch programs, or they grew up in a poor or rich neighborhood, we find minority effect estimates that are fairly homogeneous across groups. While standard errors for some of the interactions are fairly large, particularly those for small subpopulations, 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 nonminority students performing worse. The former may arise from instructors serving as role models, inspiring underrepresented students, whereas the latter may arise from group favoritism, where nonminorities, consciously or unconsciously, find it difficult to 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 nonminorities. 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 other non-whites. Doing so allows us to estimate the full set of race/ethnic interactions to determine which kinds of social interactions matter the most. Online Appendix Table 7 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 a different racial type relative to being matched to an instructor of the same type. The table provides evidence that students perform better with instructors of the same race/ethnicity, both for minority or nonminority 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,

instructor across all courses is 2.86 compared with 2.85 for nonminority instructors. The standard deviation of grades is 1.20 for minority instructors and 1.15 for nonminority 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 online Appendix Figures 2 and 3, also see online Appendix Table 8 for enrollment and instructor counts across departments).

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.[25]

Interestingly, we find robust negative effects on the 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 favorably 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 behavior 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 favoritism," 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 favoritism (Sidanius, Pratto, and Rabinowitz 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.

E. *Long-Term Outcomes*

Do the social interactions we find at the course level 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 labor market outcomes such as retention, degree completion, and transferring to four-year colleges? Table 6 reports estimates for these long-term outcomes. Because we only have one observation per student for aggregate outcomes, we cannot estimate models that include classroom or student fixed effects. Instead, we start with a model that includes a rich set of student and instructor controls, year dummies for the first term of enrollment, and the number of courses taken in the first term. 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 because students have more limited information on instructors in their first term. Furthermore, results would be confounded by dynamic accumulation effects otherwise. To address endogeneity concerns that arise because of aggregation, we also estimate a model where, in the spirit of matching estimators, a set of fixed effects for each set of courses taken in the first term is included. Since students taking the exact same set of courses in their

[25] 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.

Table 6—Estimated Role of Instructor Minority Status for Long-Term Outcomes

	Main model	Course FE model	IV model
Retention			
Observations	14,899		
Minority interaction	0.092***	0.103**	0.878***
	(0.033)	(0.044)	(0.218)
Obtain degree			
Observations	15,342		
Minority interaction	0.058**	0.066*	0.366**
	(0.028)	(0.036)	(0.182)
Transfer to four-year college			
Observations	15,341		
Minority interaction	−0.059	−0.129***	0.422**
	(0.036)	(0.046)	(0.234)
Transfer to four-year college (only include Cal State and UC campuses)			
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 at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

first term are assigned the same fixed effect we compare individuals that "look very similar" with respect to their behavior at college entry. The third 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 due to, for example, sabbatical leaves, new hires, variability in the temporary lecturer pool, and retirements.[26]

The first outcome examined is an indicator variable for whether the student remains at the college over the next two quarters. The selection-on-observables

[26] The instrumental variable is equal to the difference between the minority share of instructors in that department and term 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.

model reported in column 1 of Table 6 suggests that raising the share of minority instructors by 1 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.[27] 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 1 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 four-year college, however, is mixed. We find a small and insignificant estimate in column 1 of Table 6, but negative and positive estimates in the remaining two specifications. When estimating effects on transferring only to University of California 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.

IV. Conclusion

Using a unique administrative dataset that matches student course outcomes to instructor's race and ethnicity, 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 enrollment options among low registration priority students at a very popular and diverse community college, by restricting the variation in instructor minority status across classes within term or year, and by examining students who do not enroll in the course section of their 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 achievement gaps, representing 20–50 percent 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,

[27] Our earlier baseline results indicate that conditioning on observable student background characteristics leads to similar estimates as when using student fixed effects, and estimates from models with classroom and student fixed effects are similar to those with course and student fixed effects. These findings suggest that remaining selection bias in our long-term results from not being able to include classroom fixed effects may be small.

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 that 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 using 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 behavior, 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 nonminority 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.

REFERENCES

Abowd, John M., Robert H. Creecy, and Francis Kramarz. 2002. "Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data." U.S. Census Bureau Paper TR-2002-06.

Abowd, John M., Francis Kramarz, and David N. Margolis. 1999. "High Wage Workers and High Wage Firms." *Econometrica* 67 (2): 251–333.

Altonji, Joseph. G., and Rebecca M. Blank. 1999. "Race and Gender in the Labor Market." In *Handbook of Labor Economics*. Vol. 3C, edited by Orley C. Ashenfelter and David Card, 3143–3260. Amsterdam: Elsevier B.V.

Andrews, Martyn J., Len Gill, Thorsten Schank, and Richard Upward. 2008. "High Wage Workers and Low Wage Firms: Negative Assortative Matching or Limited Mobility Bias?" *Journal of the Royal Statistical Society: Series A* (*Statistics in Society*) 171 (3): 673–97.

Arcidiacono, Peter, Esteban M. Aucejo, and Ken Spenner. 2011. "What Happens After Enrollment? An Analysis of the Time Path of Racial Differences in GPA and Major Choice." Unpublished.

Austen-Smith, David, and Roland G. Fryer, Jr. 2005. "An Economic Analysis of 'Acting White.'" *Quarterly Journal of Economics* 120 (2): 551–83.

Bar, Talia, and Asaf Zussman. 2012. "Partisan Grading." *American Economic Journal: Applied Economics* 4 (1): 30–48.

Bettinger, Eric P., and Bridget Terry Long. 2005. "Do Faculty Serve as Role Models? The Impact of Instructor Gender on Female Students." *American Economic Review* 95 (2): 152–57.

California Community Colleges Chancellor's Office (**CCCCO**)**.** 2009. "Accountability Reporting for the California Community Colleges." A Report to the Legislature, Pursuant to AB 1417 (Pacheco, Stat. 2004, Ch. 581).

Cameron, A. Colin, and Douglas L. Miller. 2013. "A Practitioner's Guide to Cluster-Robust Inference." Unpublished.

Card, David. 1999. "The Causal Effect of Education on Earnings." In *Handbook of Labor Economics*. Vol. 3A, edited by Orley C. Ashenfelter and David Card, 1801–63. Amsterdam: Elsevier Science B.V.

Card, David, and Jesse Rothstein. 2007. "Racial Segregation and the Black-White Test Score Gap." *Journal of Public Economics* 91 (11-12): 2158–84.

Carrell, Scott E., Marianne E. Page, and James E. West. 2010. "Sex and Science: How Professor Gender Perpetuates the Gender Gap." *Quarterly Journal of Economics* 125 (3): 1101–44.

Carrington, Bruce, Peter Tymms, and Christine Merrel. 2008. "Role Models, School Improvement and the "Gender Gap"—Do Men Bring out the Best in Boys and Women the Best in Girls?" *British Educational Research Journal* 34 (3): 315–27.

Cornelissen, Thomas. 2008. "The Stata Command Felsdvreg to Fit a Linear Model with Two High-Dimensional Fixed Effects." *Stata Journal* 8 (2): 170–89.

Dee, Thomas S. 2004. "Teachers, Race, and Student Achievement in a Randomized Experiment." *Review of Economics and Statistics* 86 (1): 195–210.

Dee, Thomas S. 2005. "A Teacher Like Me: Does Race, Ethnicity, or Gender Matter?" *American Economic Review* 95 (2): 158–65.

Dee, Thomas S. 2007. "Teachers and the Gender Gaps in Student Achievement." *Journal of Human Resources* 42 (3): 528–54.

Ehrenberg, Ronald G., Daniel D. Goldhaber, and Dominic J. Brewer. 1995. "Do Teachers' Race, Gender, and Ethnicity Matter? Evidence from the National Educational Longitudinal Study of 1988." *Industrial and Labor Relations Review* 48 (3): 547–61.

Fairlie, Robert, Florian Hoffmann, and Philip Oreopoulos. 2014. "A Community College Instructor Like Me: Race and Ethnicity Interactions in the Classroom." National Bureau of Economic Research Working Paper 17381.

Fairlie, Robert W., Florian Hoffmann, and Philip Oreopoulos. 2014. "A Community College Instructor Like Me: Race and Ethnicity Interactions in the Classroom: Dataset." *American Economic Review*. http://dx.doi.org/10.1257/aer.104.8.2567.

Fry, Richard. 2002. "Latinos in Higher Education: Many Enroll, Too Few Graduate." Pew Hispanic Center Report.

Fryer, Roland G. Jr. 2011. "Racial Inequality in the 21st Century: The Declining Significance of Discrimination." In *Handbook of Labor Economics*. Vol. 4B, edited by David Card and Orley C. Ashenfelter, 855–971. Amsterdam: Elsevier B.V.

Fryer, Roland G., Jr., and Steven D. Levitt. 2004. "Understanding the Black-White Test Score Gap in the First Two Years of School." *Review of Economics and Statistics* 86 (2): 447–64.

Fryer, Roland G., Jr., and Steven D. Levitt. 2006. "The Black-White Test Score Gap through Third Grade." *American Law and Economics Review* 8 (2): 249–81.

Fryer, Roland G., Jr., and Steven D. Levitt. 2013. "Testing for Racial Differences in the Mental Ability of Young Children." *American Economic Review* 103 (2): 981–1005.

Graham, Bryan S., Guido W. Imbens, and Geert Ridder. 2009. "Complementarity and Aggregate Implications of Assortative Matching: A Nonparametric Analysis." National Bureau of Economic Research Working Paper 14860.

Hanushek, Eric A., and Steven G. Rivkin. 2008. "Harming the Best: How Schools Affect the Black-White Achievement Gap." National Bureau of Economic Research Working Paper 14211.

Hoffmann, Florian, and Phillip Oreopoulos. 2009. "A Professor Like Me: The Influence of Instructor Gender on University Achievement." *Journal of Human Resources* 44 (2): 479–94.

Holmlund, Helena, and Krister Sund. 2008. "Is the Gender Gap in School Performance Affected by the Sex of the Teacher?" *Labour Economics* 15 (1): 37–53.

Jencks, Christopher, and Meredith Phillips. 1998. *The Black-White Test Score Gap*. Washington, DC: Brookings Institution Press.

Krueger, Alan B., and Dianne M. Whitmore. 2002. "Would Smaller Classes Help Close the Black-White Achievement Gap?" In *Bridging the Achievement Gap*, edited by John E. Chubb and Tom Loveless, 11–46. Washington, DC: Brookings Institute Press.

Lahelma, Elina. 2000. "Lack of Male Teachers: A Problem for Students or Teachers?" *Pedagogy, Culture & Society* 8 (2): 173–86.

Lavy, Victor, and Analia Schlosser. 2011. "Mechanisms and Impacts of Gender Peer Effects at School." *American Economic Journal: Applied Economics* 3 (2): 1–33.

Lee, David S. 2009. "Training, Wages, and Sample Selection: Estimating Sharp Bounds on Treatment Effects." *Review of Economic Studies* 76 (3): 1071–1102.

Nixon, Lucia A., and Michael D. Robinson. 1999. "The Educational Attainment of Young Women: Role Model Effects of Female High School Faculty." *Demography* 36 (2): 185–94.

Reardon, Sean F., and Claudia Galindo. 2009. "The Hispanic-White Achievement Gap in Math and Reading in the Elementary Grades." *American Educational Research Journal* 46 (3): 853–91.

Rothstein, Jesse, and Nathan Wozny. 2011. "Permanent Income and the Black-White Test Score Gap." National Bureau of Economic Research Working Paper 17610.

Sengupta, Ria, and Christopher Jepsen. 2006. "California's Community College Students." *Public Policy Institute of California, California Counts: Population Trends and Profiles* 8 (2).

Sidanius, Jim, Felicia Pratto, and Joshua L. Rabinowitz. 1994. "Gender, Ethnic Status, and Ideological Asymmetry: A Social Dominance Interpretation." *Journal of Cross-Cultural Psychology* 25 (2): 194–216.

Tajfel, Henri, and John C. Turner. 1979. "An Integrative Theory of Intergroup Conflict." *The Social Psychology of Intergroup Relations*, edited by William G. Austin and Stephen Worchel, 33–47. Monterey, CA: Brooks-Cole.

US Department of Education. 2010. *Digest of Education Statistics 2009*. Washington, DC: National Center for Education Statistics, Institute of Education Sciences.

Wilson, Stacy, Mallory Newell, and Ryan Fuller. 2010. "Ready or Not, Here They Come: California State University Undergraduate Demand Projections, 2009–2019." California Postsecondary Education Commission Report 10-05.

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4. Mette Trier Damgaard, Helena Skyt Nielsen. Behavioral economics and nudging in education: evidence from the field 21-35. [Crossref]
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6. Shana Sanam Khan. 2019. Standardized Entrance/Aptitude Testing in the Era of Foucault's Panopticon: The Bilingual Student and the Minority Student. *Education and Urban Society* **39**, 001312451989497. [Crossref]
7. Jan Feld, Nicolás Salamanca, Ulf Zölitz. 2019. Students are almost as effective as professors in university teaching. *Economics of Education Review* **73**, 101912. [Crossref]
8. Marcella Alsan, Owen Garrick, Grant Graziani. 2019. Does Diversity Matter for Health? Experimental Evidence from Oakland. *American Economic Review* **109**:12, 4071-4111. [Abstract] [View PDF article] [PDF with links]
9. Luke J. Lara. 2019. Faculty of Color Unmask Color-Blind Ideology in the Community College Faculty Search Process. *Community College Journal of Research and Practice* **43**:10-11, 702-717. [Crossref]
10. Stephen B. Holt, Seth Gershenson. 2019. The Impact of Demographic Representation on Absences and Suspensions. *Policy Studies Journal* **47**:4, 1069-1099. [Crossref]
11. Jasmín D. Llamas, Khoa Nguyen, Alisia G.T.T. Tran. 2019. The case for greater faculty diversity: examining the educational impacts of student-faculty racial/ethnic match. *Race Ethnicity and Education* **3**, 1-17. [Crossref]
12. Dominique J. Baker, Benjamin T. Skinner, Christopher H. Redding. 2019. Affirmative Intervention to Reduce Stereotype Threat Bias: Experimental Evidence from a Community College. *The Journal of Higher Education* **69**, 1-33. [Crossref]
13. Lindy Hern, Remi McKay, Susan Brown. 2019. "We Need Community": Assessing the Impact of Faculty, Advising, Campus Social Life, and Racial Formation on the Transfer Student Experience at a Diverse Island Campus. *Journal of Applied Social Science* **13**:2, 115-138. [Crossref]
14. Son-Thierry Ly, Eric Maurin, Arnaud Riegert. 2019. A pleasure that hurts: the ambiguous effects of elite tutoring on underprivileged high school students. *Journal of Labor Economics* . [Crossref]
15. Michael A. Gottfried, J. Jacob Kirksey, Adam Wright. 2019. Same-Race Student–Teacher: Comparing Outcomes for Kindergartners With and Without Disabilities. *Remedial and Special Education* **40**:4, 225-235. [Crossref]
16. Joseph Vecci, Tomáš Želinský. 2019. Behavioural challenges of minorities: Social identity and role models. *PLOS ONE* **14**:7, e0220010. [Crossref]
17. Amanda Bayer, David W. Wilcox. 2019. The unequal distribution of economic education: A report on the race, ethnicity, and gender of economics majors at U.S. colleges and universities. *The Journal of Economic Education* **50**:3, 299-320. [Crossref]

18. James V. Koch, Ziniya Zahedi. 2019. The effects of role models on college graduation rates. *Journal of Economics and Finance* **43**:3, 607-617. [Crossref]

19. Marit Hinnosaar. 2019. Gender inequality in new media: Evidence from Wikipedia. *Journal of Economic Behavior & Organization* **163**, 262-276. [Crossref]

20. Chayla Haynes, Lori D. Patton. 2019. From Racial Resistance to Racial Consciousness: Engaging White STEM Faculty in Pedagogical Transformation. *Journal of Cases in Educational Leadership* **22**:2, 85-98. [Crossref]

21. Dario Sansone. 2019. Teacher Characteristics, Student Beliefs, and the Gender Gap in STEM Fields. *Educational Evaluation and Policy Analysis* **41**:2, 127-144. [Crossref]

22. Amanda L. Griffith, Joyce B. Main. 2019. First impressions in the classroom: How do class characteristics affect student grades and majors?. *Economics of Education Review* **69**, 125-137. [Crossref]

23. Susan Payne Carter, Whitney Dudley, David S. Lyle, John Z. Smith. 2019. Who's the Boss? The effect of strong leadership on employee turnover. *Journal of Economic Behavior & Organization* **159**, 323-343. [Crossref]

24. Steven Bednar, Dora Gicheva. 2019. Workplace Support and Diversity in the Market for Public School Teachers. *Education Finance and Policy* **14**:2, 272-297. [Crossref]

25. Naureen Karachiwalla. 2019. A Teacher Unlike Me: Social Distance, Learning, and Intergenerational Mobility in Developing Countries. *Economic Development and Cultural Change* **67**:2, 225-271. [Crossref]

26. Chris Birdsall, Seth Gershenson, Raymond Zuniga. 2018. The Effects of Demographic Mismatch in an Elite Professional School Setting. *Education Finance and Policy* **38**, 1-30. [Crossref]

27. Di Xu, Qiujie Li. 2018. Gender achievement gaps among Chinese middle school students and the role of teachers' gender. *Economics of Education Review* **67**, 82-93. [Crossref]

28. John M. Carey, Kevin R. Carman, Katherine P. Clayton, Yusaku Horiuchi, Mala Htun, Brittany Ortiz. 2018. Who wants to hire a more diverse faculty? A conjoint analysis of faculty and student preferences for gender and racial/ethnic diversity. *Politics, Groups, and Identities* **94**, 1-19. [Crossref]

29. Jeanne Lafortune, Julio Riutort, José Tessada. 2018. Role Models or Individual Consulting: The Impact of Personalizing Micro-entrepreneurship Training. *American Economic Journal: Applied Economics* **10**:4, 222-245. [Abstract] [View PDF article] [PDF with links]

30. Ela Joshi, Sy Doan, Matthew G. Springer. 2018. Student-Teacher Race Congruence: New Evidence and Insight From Tennessee. *AERA Open* **4**:4, 233285841881752. [Crossref]

31. Sabrina M. Solanki, Di Xu. 2018. Looking Beyond Academic Performance: The Influence of Instructor Gender on Student Motivation in STEM Fields. *American Educational Research Journal* **55**:4, 801-835. [Crossref]

32. Jie Gong, Yi Lu, Hong Song. 2018. The Effect of Teacher Gender on Students' Academic and Noncognitive Outcomes. *Journal of Labor Economics* **36**:3, 743-778. [Crossref]

33. Andrew J. Hill, Daniel B. Jones. 2018. A teacher who knows me: The academic benefits of repeat student-teacher matches. *Economics of Education Review* **64**, 1-12. [Crossref]

34. Mette Trier Damgaard, Helena Skyt Nielsen. 2018. Nudging in education. *Economics of Education Review* **64**, 313-342. [Crossref]

35. Lester Lusher, Doug Campbell, Scott Carrell. 2018. TAs like me: Racial interactions between graduate teaching assistants and undergraduates. *Journal of Public Economics* **159**, 203-224. [Crossref]

36. Travis J. Bristol. 2018. To Be Alone or in a Group: An Exploration Into How the School-Based Experiences Differ for Black Male Teachers Across One Urban School District. *Urban Education* **53**:3, 334-354. [Crossref]

37. Anna J. Egalite, Brian Kisida. 2018. The Effects of Teacher Match on Students' Academic Perceptions and Attitudes. *Educational Evaluation and Policy Analysis* **40**:1, 59-81. [Crossref]
38. Katie Vinopal. 2018. Understanding Individual and Organizational Level Representation: The Case of Parental Involvement in Schools. *Journal of Public Administration Research and Theory* **28**:1, 1-15. [Crossref]
39. Andrew Hill, Daniel Jones, Lindsey Woodworth. 2018. A Doctor Like Me: Physician-Patient Race-Match and Patient Outcomes. *SSRN Electronic Journal* . [Crossref]
40. My Nguyen. 2018. The Relationship between Race-Congruent Students and Teachers: Does Racial Discrimination Exist?. *SSRN Electronic Journal* . [Crossref]
41. Lauren Russell. 2017. Can learning communities boost success of women and minorities in STEM? Evidence from the Massachusetts Institute of Technology. *Economics of Education Review* **61**, 98-111. [Crossref]
42. Diyi Li, Cory Koedel. 2017. Representation and Salary Gaps by Race-Ethnicity and Gender at Selective Public Universities. *Educational Researcher* **46**:7, 343-354. [Crossref]
43. Constance A. Lindsay, Cassandra M. D. Hart. 2017. Exposure to Same-Race Teachers and Student Disciplinary Outcomes for Black Students in North Carolina. *Educational Evaluation and Policy Analysis* **39**:3, 485-510. [Crossref]
44. Chris Muris. 2017. Estimation in the Fixed-Effects Ordered Logit Model. *The Review of Economics and Statistics* **99**:3, 465-477. [Crossref]
45. Briggs Depew, Ozkan Eren, Naci Mocan. 2017. Judges, Juveniles, and In-Group Bias. *The Journal of Law and Economics* **60**:2, 209-239. [Crossref]
46. Seth Gershenson, Alison Jacknowitz, Andrew Brannegan. 2017. Are Student Absences Worth the Worry in U.S. Primary Schools?. *Education Finance and Policy* **12**:2, 137-165. [Crossref]
47. Adam Wright, Michael A. Gottfried, Vi-Nhuan Le. 2017. A Kindergarten Teacher Like Me. *American Educational Research Journal* **54**:1_suppl, 78S-101S. [Crossref]
48. Steven Bednar, Dora Gicheva. 2017. Workplace Support and Diversity in the Market for Public School Teachers. *SSRN Electronic Journal* . [Crossref]
49. Jan Feld, Nicolas Salamanca, Ulf ZZlitz. 2017. Students Are Almost as Effective as Professors in University Teaching. *SSRN Electronic Journal* . [Crossref]
50. Michhle MMller-Itten, Aniko Oery. 2017. Mentoring and the Dynamics of Affirmative Action. *SSRN Electronic Journal* . [Crossref]
51. Eva Feron, Trudie Schils, Bas ter Weel. 2016. Does the Teacher Beat the Test? The Value of the Teacher's Assessment in Predicting Student Ability. *De Economist* **164**:4, 391-418. [Crossref]
52. Amanda Bayer, Cecilia Elena Rouse. 2016. Diversity in the Economics Profession: A New Attack on an Old Problem. *Journal of Economic Perspectives* **30**:4, 221-242. [Abstract] [View PDF article] [PDF with links]
53. Charles M. Becker, Cecilia Elena Rouse, Mingyu Chen. 2016. Can a summer make a difference? The impact of the American Economic Association Summer Program on minority student outcomes. *Economics of Education Review* **53**, 46-71. [Crossref]
54. Donna K. Ginther, Shulamit Kahn, Walter T. Schaffer. 2016. Gender, Race/Ethnicity, and National Institutes of Health R01 Research Awards. *Academic Medicine* **91**:8, 1098-1107. [Crossref]
55. Seth Gershenson, Stephen B. Holt, Nicholas W. Papageorge. 2016. Who believes in me? The effect of student–teacher demographic match on teacher expectations. *Economics of Education Review* **52**, 209-224. [Crossref]

56. Mark Maier, W. Edward Chi. 2016. Community college economics instruction: Results from a National Science Foundation Project. *The Journal of Economic Education* **47**:1, 84-88. [Crossref]
57. Joe Vecci, Tomas Zelinsky. 2016. Social Identity and Role Models. *SSRN Electronic Journal* . [Crossref]
58. Jie Gong, Yi Lu, Hong Song. 2016. The Effect of Teacher Gender on Students' Academic and Noncognitive Outcomes. *SSRN Electronic Journal* . [Crossref]
59. Jimmy Ellis, Seth Gershenson. 2016. LATE for the Meeting: Gender, Peer Advising, and College Success. *SSRN Electronic Journal* . [Crossref]
60. Naureen Karachiwalla. 2015. A Teacher Unlike Me: Social Distance, Learning, and Intergenerational Mobility in Developing Countries. *SSRN Electronic Journal* . [Crossref]
61. Marit Hinnosaar. 2015. Gender Inequality in New Media: Evidence from Wikipedia. *SSRN Electronic Journal* . [Crossref]
62. Michael S. Kofoed, Elizabeth McGovney. 2015. The Effect of Same-Gender and Same-Race Role Models on Occupation Choice: Evidence from Randomly Assigned Mentors at West Point. *SSRN Electronic Journal* . [Crossref]