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Racial and Gender Inequality in Human Capital: Evidence From Social Interactions Among Community College and University of California Students

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RACIAL AND GENDER INEQUALITY IN HUMAN CAPITAL: EVIDENCE FROM SOCIAL INTERACTIONS AMONG COMMUNITY COLLEGE AND UNIVERSITY OF CALIFORNIA STUDENTS

A dissertation submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Daniel M. Oliver

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Abstract

RACIAL AND GENDER INEQUALITY IN HUMAN CAPITAL:

EVIDENCE FROM SOCIAL INTERACTIONS AMONG COMMUNITY

COLLEGE AND UNIVERSITY OF

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This dissertation focuses on social interactions in classrooms to assess the extent that race and gender of classmates and graduate teaching assistants (TAs) affect student outcomes in behavior and performance. Two chapters rely on quasi-experimental variations for social interactions while the third relies on a randomized experiment.

The first chapter utilizes administrative data from a large California community college. I examine whether minority students are affected by the race and ethnicity of classmates. To identify social interactions, I leverage classroom level enrollment variations in racial and ethnic compositions on more than 186,000 course enrollments by 83,000 first-time students with limited class choices. The setting and richness of the data provide a robust examination of interactions with the inclusion of individual and class fixed effects. I find that Hispanic and African-American students are more likely to persist in, pass classes, and continue with the same course subject when there are more classmates of their own race and ethnicity. This is especially true for Hispanic

students in courses that are transferable to the University of California and California State University systems.

The second chapter is the first-ever large-scale experiment of interactions between female and male students in an important gateway course for the Sciences. Universities around the world struggle to attract more women into STEM fields. A major concern is that female students face gender bias, discrimination, and related barriers in male-dominated STEM fields. To investigate this concern, we randomly paired every student enrolled in an introductory Chemistry lab (3,902 students and total N=5,537) over the past four years at a large public research university. Although students work very closely the entire term in the labs, we find no evidence that female students react negatively to male students. When assigned a male partner, female students do not receive lower scores or grades, and they are no more likely to drop the course, or lose interest in continuing in a STEM field. We also find no evidence that academically weaker female students are negatively affected by male students and no evidence that female students are negatively affected when paired with academically stronger male students.

The third study explores how a lack of minority role models affects the post-secondary STEM achievement gap between minority and non-minority students. I leverage a quasi-experimental setting in introductory Chemistry labs to estimate the extent the race of TAs affect student performance and decisions. Although I do not detect effects on grade performance, I detect that a racial match between students and instructors decreases the probability of dropping a course by 1.2 percentage points (on a base rate of 5.0 percent). This suggests that the race of TAs is an important component in student decisions to persist in science.

To my parents and grandparents.

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I thank my family for their support and dedication in preparing me for research. Their commitment to helping me focus will be remembered. I also thank my advisers for modeling the resilience required to teach and conduct research. I gained humility and confidence from their methodological push to understand fundamentals for any concept, project, or task. Finally, I thank my neighbors. Living in a community that fosters humanity with careful thought and action has been a joy. They have carried me through tougher days by being their everyday self.

Chapter 1

Classmates Like Me: Race and Ethnicity in College

1.1 Introduction

Large racial and ethnic achievement gaps continue to persist at post-secondary institutions in the United States. 39.5% of Black and 48.6% of Hispanic students who start at any type of college or university complete a degree or certificate within six years while White and Asian students complete at rates of 66.2% and 68.9%.[1] These gaps in post-secondary achievement contribute to long-term income inequalities (Altonji & Blank, 1999). The current earnings premium for bachelor degree and associate degree holders relative to high school graduates are correspondingly $37,000 and $9,000.[2][3]

[1]National Student Clearinghouse, Signature Report, Shapiro et al. (2017)

[2]The Hamilton Project, Brookings Institute, Shambaugh, Bauer, and Breitwieser (2018).

[3]Career technical certificates and degrees at California community colleges also provide average returns between 14 and 45 percent (Stevens, Kurlaender, & Grosz, 2018).

While pre-enrollment characteristics of minorities are a major component of the achievement gap, the selection and role of post-secondary institutions are also important (Fry, 2004; Arcidiacono & Koedel, 2014; Flores, Park, & Baker, 2017). A critical aspect in academic achievement is a sense of belonging to the social environment (Baumeister & Leary, 1995; Akerlof & Kranton, 2002; Strayhorn, 2012). Seeing few or many similar classmates are important in this regard. In this study, I estimate the extent to which minority students are affected by unanticipated variations in the racial and ethnic composition of their classmates at an institution where minority students are underrepresented.

I study a setting where it is difficult for students to self-select their peers. The college of interest is an over-subscribed campus.[4] The subjects of this study are first-time ever college students. These students are the least likely to be informed about compositional makeup of students in classes. They are also by default placed on the lowest priority for registration.[5] Among students with a low registration priority only 54.9 percent of the classes in which students first attempt to register result in actual enrollment.[6]

While it is unlikely that these students self-select classmates, they must select courses. I control for this issue in two manners. First, the parameter of interest is

[4]This campus has received both local and national attention on impaction and the waitlisted students. The San Jose Mercury News reports that "De Anza College is preparing for a spike in enrollment this fall that may be so high, some students will be turned away from classes at the Cupertino campus." The New York Times reports that "at De Anza College in Cupertino, Calif., about 8,000 students found themselves on wait lists last month."

[5]Students enrolled in special focused programs such as SLAM, STARS, and SSRC receive special registration priority status. These students are restricted from the analysis.

[6]Estimates are from Fairlie, Hoffmann, and Oreopoulos (2014).

the differential effect between minority and non-minority students in the same exact class. To further address biases that may exist, the analysis examines combinations of individual, class, and course-by-race fixed effects. The use of individual fixed effects rules out bias from unobservable student characteristics such as ability and motivation. Class fixed effects controls for every characteristic related to a specific class. This includes all classmate characteristics such as their abilities, and the term, location, time, subject, class size, instructor, assessments, and common-shocks. Course-by-race fixed effects controls for preferences and comparative advantages by race in a course.

This paper distinguishes itself from previous studies on social interactions at the post-secondary level by being the first to estimate the effect of classroom racial compositions on minority students across a universe of courses within a post-secondary institution. I utilize a novel data set which contains comprehensive background information on students and instructors for each class, course-level academic outcome, and student course-level data.[7] The extent to which underrepresented minorities are affected by racial compositions in the classroom is estimated from this detailed administrative data. The term “underrepresented minority”, which I use interchangeably with “minority” includes African-Americans, Hispanics, and Native-Americans/Pacific-Islanders.[8] By examining students across classrooms within an institution, I rule out an extensive set of institutional factors that may influence the behaviors of students unrelated to classmates. These include but are not limited to the location, type of institution, so-

[7]Each class is unique to instructor and student compositions. Over 32,000 classes are observed.

[8]This is the definition used for “underrepresented minority” by the National Science Foundation and California public higher education.

cial programming (e.g. admission policies, sports teams, student services, and social initiatives), and campus leadership.

There are many potential explanations for effects stemming from the racial compositions of classmates, positive and negative. First, students may expect in-group and out-group behaviors that cause them to feel more comfortable in an environment with more in-group members (Tajfel & Turner, 1979; Chen & Li, 2009). Friendship and study partner formations may also occur along racial and ethnic identities (Marmaros & Sacerdote, 2006; Mayer & Puller, 2008). Second, teachers may adjust their instruction based on student characteristics in their classrooms and students may anticipate this action (Duflo, Dupas, & Kremer, 2011). Third, African-American and Hispanic students in academic environments with large minority student populations may not perform to their academic potential because they fear accusations of "acting white" (Fordham & Ogbu, 1986; Fryer Jr & Torelli, 2010). There are no clear theoretical predictions on the sign or magnitude of the overall effects of classmate racial compositions, thus I provide a starting point with empirical estimates.

I detect that minority students respond to unanticipated increases in the share of classmates with similar racial/ethnic identities. When students are in classes with relatively larger proportions of similar racial/ethnic classmates, they are less likely to drop the class; in addition, these students are more likely to take a course in the same subject during the subsequent term, pass more classes, and return to the same college the next term. Specifically, I estimate that Hispanic students are 1.3 percentage points (on a sample base of 19.1 percent) less likely to drop, and 1.2 percentage points (on a sample base of 61.1 percent) more likely to earn course credit as a result of a 10 percentage point increase in exposure to classmates with a similar race/ethnicity. The effects on passing for Hispanics are driven by courses transferable to University of California (UC) and California State University (CSU) systems. For African-American students, I detect that they are 2.5 percentage points less likely to drop when their representation increases by 10 percentage points. This affects the number of classes they pass by 0.04 classes (on a sample base of 1.95 classes) and their probability of returning to school by 1.1 percentage points (on a sample base of 61.9 percent) as a result of a 10 percentage point increase in exposure to similar classmates. In the spirit of intersectionality, I examine whether there are differential effects on minorities by gender and socioeconomic status by zipcode income levels. I find that African-American women are differentially more likely to pass a class compared to their counterparts with the same race/ethnicity.

This study provides timely insights and evidence that racial and ethnic compositions in social organizations are important for addressing minority gaps in recruitment and retention of underrepresented minorities. Consistent with marginality, the estimated effects are generally larger for the less represented minority group (African-American students). To my knowledge there are no other quasi-experimental studies using administrative data on working age adults that have examined the effects of racial compositions among peers on retention and achievement at a large social organization.

The rest of the paper proceeds as follows: Section 2 starts by providing a background on social interactions and what has been inferred from racial interactions in higher education. The next section discusses the institutional background of the study and summarizes the data. Section 1.4 introduces the econometric framework and tests for sorting. Section 1.5 presents results on racial interactions in educational outcomes. The final section concludes.

1.2 Existing Literature

The estimation of causal effects stemming from social interactions at the post-secondary level is difficult. College students in all but a few cases are free to choose classes, majors, and other social environments. These choices make it difficult to separate selection bias from effects of social interactions (Sacerdote, 2001).[9] The elimination of the selection problem may still pose endogenous issues if outcome on outcome regression strategies are used (Manski, 1993; Carrell, Fullerton, & West, 2009; Angrist, 2014). Endogeneity may occur as a result of reflection (Manski, 1993) or common shocks (Lyle, 2007; Angrist, 2014). In both cases, inference is unlikely to be credible because the source and magnitude of causation is unclear when only the outcomes are observed. To address these identification issues researchers primarily rely on pre-determined and well measured characteristics (Angrist, 2014).

The literature on social interactions in post-secondary academic environments (henceforth referred to as the existing literature) has examined the interaction of students with instructors (Borjas, 2000; Bettinger & Long, 2005; Carrell, Page, & West, 2010; Hoffmann & Oreopoulos, 2009; Fairlie et al., 2014; Solanki & Xu, 2018), teaching assistants (Lusher, Campbell, & Carrell, 2018), section-mates (Feld & Zölitz, 2017; Dills,

[9]Sacerdote (2001) specifically refers to these as peer effects in his setting because he studies peers.

2018), tutorial groups (Booij, Leuven, & Oosterbeek, 2017), and classmates (Fischer, 2017). Only Fairlie et al. (2014) and Dills (2018) have examined the effects related to interactions of minorities in post-secondary academic environments.[10] This is surprising in the historical context of racial discrimination in education (e.g. Brown v. Board of Education of Topeka, 1954). In Fairlie et al. (2014), they examine the interaction between minority students and minority community college instructors. The researchers rely on quasi-experimental matching of instructors and students while utilizing a combination of student and class fixed effects as controls. They find that the academic persistence and performance of minority students improve when matched with a minority instructor. Lusher et al. (2018) study similar interactions between teaching assistants (TAs) and students in economics courses at a research university. Their identification relies on unannounced TA assignments to courses. They study the effects of the share of Asian teaching assistants on Asian students. Both studies share similar findings in regard to improved academic performance and decisions to stay in classes or attend sections with similar race/ethnicity instructors and teaching assistants.

Prior to this study, evidence of the effects of Black and Hispanic peers in post-secondary academic environments has solely hinged on sections for a course sequence in the development of western civilization (DWC) at a Catholic liberal arts college. To identify effects from racial/ethnic compositions, Dills (2018) relies on 4,445 first-term students exogenously assigned to sections that average 67 students. Although Dills finds evidence that Black and Hispanic students earn lower grades as minority

[10] Alternatively, affirmative action has been extensively examined. For a review see Arcidiacono and Lovenheim (2016).

representation increases in sections, the researcher does not detect differences in drops or group switching when opportunities of groups switching are provided.

1.3 Data

1.3.1 Data Sources and Institutional Background

The 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 114 colleges and 2.1 million students per year. De Anza College has an average total enrollment of 16,000 students per year. It has a larger share of minority students than the nationally representative community college, reflecting the diversity of Northern California. The college is on the quarter system and the majority of classes are 50 or fewer students. The tuition at De Anza College is $31 per unit (roughly $1,515 per year in tuition and fees) with a large percentage of students receiving fee waivers because of financial need. Similar to all community colleges in California it has open enrollment. Anyone with a high school diploma or equivalent is automatically admitted.

The data-set includes an extensive set of course outcomes as well as detailed demographic characteristics of every student registered at the community college from the fall quarter of 2002 to the spring quarter of 2010. The data on each individual student shows course registrations, dropouts, withdraws, recorded grades, credits earned, and demographic characteristics of their instructor.[11] A student's registration priority together with any registration attempt is recorded at the beginning of each quarter. The course-level data-set allows for observations of students enrolled before their first day of the term, regardless of whether they completed the class.

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

1.3.2 Sample Restrictions and Summary Statistics

I exclude orientation courses, online courses, and classrooms with enrollments of less than 15 students or more than 100 students to observe common classroom settings.[12] This represents an exclusion of 9.2 percent of observations. In the main sam-

[11] A student who drops or is dropped from a course during the first three weeks of the term is considered the same as never attending on academic records. Alternatively, a withdrawal is an official record. It is assigned to drops from the end of the third week of the term through the end of the eighth week. After the eighth week, a student can only be a granted a W by means of a petition.

[12] My estimated results are similar when I trim the class sizes.

ple, I only analyze outcomes for first-time college students who are in their first term with the lowest registration priority and report an ethnicity/race of White, Asian, Hispanic, African-American, or Native-American/Pacific-Islander. This remaining sample accounts for 186,336 classroom-student observations. Table 1.1 reports descriptive statistics. In panel A the summary of characteristics of students are displayed. Asians are most represented (46%), followed by Whites (28%). The minority groups are less represented. Hispanics account for 17% while African-Americans account for 6%. The remaining 3% is accounted for by Native-Americans and Pacific-Islanders.

Panel B in Table 1.1 reports the primary outcomes of interest. Included are drops, withdraws, passing, grade points earned (where 4.0 is equivalent of an A), total number of classes passed during the first term, taking same subject courses the subsequent term, and returning the subsequent term. The largest differences between minorities and non-minorities occur along the dimensions of passing for course credit, the grade that they earn, and the number of classes they pass. White and Asian students have an average pass rate near 88% while minorities have a pass rate that is approximately 78%. Across outcomes, the least represented ethnic/racial groups which include African-American and Native-American/Pacific-Islander show consistently worse performance than the well represented groups.

Panel C of Table 1.1 displays the mean classroom characteristics of the main sample. The average enrollment size for each class in this sample is 37.84 students. The average share of first-time students is approximately 17%. Included are also the shares of African-American (6%), Hispanic (12%), and Other Minorities (2%) in classes.

The representation of Hispanic enrollment at this college is slightly lower than the 16% national pattern for all colleges (Ma & Baum, 2016). Figure 1.1 displays the distribution of enrollment sizes by classroom unit observations. The peak of the distribution is close to 30 students per class. Figure 1.2 displays the distribution by minority categories. The panels on ethnicity/race show that there is a wide variation in classroom share of Hispanic students, but the variation is considerably limited for African-American students and other minorities due to their very small representation on campus. African-Americans and Native-Americans / Pacific-Islanders are frequently in classes where there are no other classmates that share their ethnicity/race.

1.4 Econometric Strategy

1.4.1 Main Model

The main model on student-classroom level outcomes is given by

$$y_{ic} = \alpha Minority_i \times MinorityClassmates_{ic} + \gamma_i + \lambda_c + \delta_{ik} + u_{ic} \tag{1.1}$$

where students are indexed by i, classes by c, and courses by k. The student variable Minority is an indicator variable for whether student i belongs to an underrepresented minority group. The student and class variable MinorityClassmates represents the underrepresented minority classmate share value for class c in which student i is enrolled. The values are between 0 and 1. Zero indicates there are no minority classmates, while a value of one represents that all classmates are minorities. Fixed effects are represented by γ_i, λ_c, δ_{ik}. They represent individual, class, and course-by-race fixed effects, respectively. The general parameter of interest is α which determines the difference in effect of minority classmates between minority and non-minority students. I refine this equation and incorporate specific minority groups to obtain the preferred empirical model:

$$y_{ic} = \alpha_1 H_i \times HCmates_{ic} + \alpha_2 AA_i \times AACmates_{ic} + \gamma_i + \lambda_c + \delta_{ik} + u_{ic} \tag{1.2}$$

where I have separated the variable Minority by H(Hispanic) and AA(African-American). Similar to the MinorityClassmates variable from equation (1.1), HCmates and AAmates represent the classmate share value by the corresponding racial/ethnic categories.[13] The α parameters separately represent the difference in effects by each minority group with non-minority students.

The interaction terms between the race/ethnicity of students and classmates allows for the use of individual and class fixed effects. This set of fixed effects help overcome the common threats to validity associated with observed and unobserved differences across students and classes. Individual fixed effects provide additional controls for unobserved student characteristics such as motivation and previous educational experiences. Class fixed effects comprehensively control for observable characteristics which include but are not limited to course, term, day/time, class size, and instructor. Unobservable classroom characteristics that are also controlled for by class fixed effects include peer quality and all common shocks such as grade curving and disruptions. Course-by-race fixed effects control for racial preferences and advantages that may exist for a course.

[13]The interaction between an indicator for other minorities (Native-American/Pacific-Islander) and share of other minorities (Native-American/Pacific-Islander) classmates are included in the regression as controls.

I estimate equation (1.2) on four student class outcome variables. They include a dummy variable for whether a student drops the class by the first three weeks of the term, a dummy variable for whether a student drops or withdraws anytime during the term, a dummy for whether a student unconditionally passes a class (e.g. regardless of dropping), and a dummy for whether they take a course in the same subject the subsequent term.

1.4.2 Cumulative and Intermediate Outcomes Model

The second set of outcomes I examine are the number of classes students pass and whether they persist to the next term. A consequence of analyzing these outcomes is that only one observed outcome can be made per student, regardless of the number of classes in which they enroll in their first-term. For this reason student fixed effects cannot be included. Instead I relax the preferred model by removing student fixed effects and include controls on gender, zipcode, and a fourth-order polynomial on age. Similar to the preferred model, I use class and course by race fixed effects. I follow Fairlie et al. (2014) to also generate course-set indicator controls. The course-set indicator variables account for realized combinations of courses first-time students have enrolled. This allows for comparisons across students that are likely to be very similar.

1.4.3 Empirical Test for Sorting

A normal concern with econometric models occurs when the identifying variation is correlated with the error term. In this case, the α parameters would be biased if highly motivated minority students sort into classes with more minorities and/or highly motivated non-minority students sort into classes with more non-minorities. This issue is largely addressed by the inclusion of individual fixed effects. This allows for comparisons to be made from the same highly motivated student across classes.

To further address the potential for sorting, I restrict the analysis to a sample of first-term ever college students who are placed on the lowest level of priority for course registration. As first-time students, they are unlikely to know or predict the racial compositions of specific classes. As the lowest enrollment priority students on campus, they are less likely to be able to enroll in the classes that are their top choice. Many classes get filled early due to the excess demand for courses at this college. Sorting is generally difficult.

When individual fixed effects are removed, sorting poses an increased threat to validity. To empirically test for sorting in this scenario, I replace the outcome variable y_{ic} with individual characteristics X_i.

$$X_i = \phi_1 H_i \times HCmates_{ic} + \phi_2 AA_i \times AACmates_{ic} + \kappa_c + \psi_{ik} + \nu_{ic} \tag{1.3}$$

The ϕ parameters provide an empirical estimate on sorting in observable characteristics based on each minority group interacted with corresponding share of similar classmates. κ and ψ represent class and course by race fixed effects, respectively. I test for sorting by class enrollment size, gender, log of age, and the median income of their home address zipcode.

Table 1.2 reports these tests without (columns 1 through 4) and with (columns

5 through 7) class fixed effects. Column 1 examines whether class enrollment size can be predicted by the specification. Column 2 examines a dummy outcome variable that describe whether an individual is a female. In both cases, the coefficients of interest show that differential changes cannot be detected as classroom racial compositions change. Column 3 and column 4 examine log of age and census reported median income at the zip-code level. Columns 5 through 7 display results with the inclusion of class fixed effects. These results combined with the restrictive nature of being a first-time student provide confidence that the regressors of interest are unbiased.

1.5 Results

1.5.1 Main Results

Estimates of minority interactions between students and their classmates for all four behavioral class outcomes are reported in Table 1.3.[14] All the reported estimates are unconditional to drops or withdrawals.[15] I examine the sensitivity of the econometric model by including different fixed effects. The inclusion of fixed effects progressively restricts the variation used to identify the parameters of interest. Column 4 reports the preferred specification from equation (1.2) which includes student, class, and course-by-race fixed effects. All columns include course-by-race fixed effects. The other specifications reported on the table include term fixed effects with student

[14]The coefficients for "Other Minorities" are not reported due to their small sample size and distinct differences between Native-Americans and Pacific-Islanders.

[15]Drops must occur within the first 3 weeks of the term. These drops are not recorded on a student's official academic history. Withdraws are drops recorded in a student's official academic history and occur after the first 3 weeks.

and class controls (column 1), class fixed effects with student controls (column 2), student fixed effects and class controls (column 3), and a specification with student, class, and race-by-instructor-race fixed effects (column 5).[16] Standard errors are clustered by course and term.

Both Hispanic and African-American students exhibit a behavior to remain in classes with higher representations of their race/ethnic group. Within the first three weeks of the term, Hispanic students compared to non-minority students are 1.3 percentage points less likely to drop a class due to a 10 percentage point increase in composition of Hispanic classmates. Correspondingly, African-American students are 2.5 percentage points less likely to drop a class due to a 10 percentage point increase in composition of African-American classmates (henceforth, estimates will be stated as relative to a 10 percentage point increase of a similar race/ethnicity). For comparison, the base drop rate for students is 19.1 percent. The estimates are robust across specifications including class and race by instructor-race fixed effects. This implies that the effects are driven by the racial composition of classmates and not other factors.

The class passing outcome provides evidence that Hispanic students are also 1.2 percentage points more likely to pass (on a base of 61.1 percent). Although I am unable to detect statistical significance for African-American students under the preferred specification, my estimates range from 1.7 to 3.1 percentage point effects. The similar magnitudes on the effect for drops and passing suggest that students are

[16] Class fixed effects implicitly control for the term because classes are unique to each term. Student fixed effects also control for the term because the identifying variation only occurs during a student's first-term.

not harmed by their decision to persist in a class.

Table 1.3 also reports the effects of similar classmates on taking the same subject the next term. The estimates for all specifications show that Hispanic and African-American students are more likely to enroll in the same subject the next term as a result of increased exposure to similar ethnicity/race in their class with a statistically significant effect of 1.0 percentage points for Hispanic students and a non-statistically significant 0.7 percentage point effect for African-American students (on a base of 30.6 percent). In order to distinguish the effect from overall institutional persistence, I restrict the sample to students who return the next term on Table 1.4. The magnitudes appear to be slightly larger and range from 0.8 to 2.2 percentage points for Hispanic students and a 0.0 to 2.0 percentage points for African-American students (on a base of 44.0 percent).

1.5.2 Robustness

Although it is unlikely that first-time students with the lowest registration priority can control their exposure to racial variations on the first days of class, non-first-time students who have high priorities in registration may sort into classrooms with unobserved racial/ethnic advantages. An example would be high-registration priority minority students sorting into minority instructor classes. I rule out this threat to validity in two manners. First, I include a race by instructor race fixed effects to the preferred model and see little or no changes in estimates. This is displayed in column 5 of Table 1.3. Additionally, I compute estimates using the preferred model using classmate share variation of first-time classmates by each minority group. Table 1.5 displays these estimates and show that they are consistent with the main results of this study.

An empirical study on minorities is generally difficult due to the literal definition of minority. Minorities are observed less often than their counterparts. This creates a circumstance where it is easier for outliers to drive estimates. This can result in a type I error where a null hypothesis is falsely rejected. I take three approaches to ensure that this is not the case. First, I winsorize to censor outliers. Second, I include classmate share interaction terms on demographic characteristics that are likely to be correlated with ethnicity and race. Finally, I provide estimates in a consistent manner to previous studies and institutional practices by pooling minority groups.[17]

I winsorize the classmate share variables for all three minority groups at the .05 level. This process censors both the lower and upper 5 percentiles of observed class shares of each minority group. Specifically, this replaces the values that are between the 0 and 5th percentiles with the 5th percentile classmate share value and values between the 95th and 100th percentile with the 95th percentile value. I ensure that the censoring applies to only 5 percent of each tail of the distribution with a random selection for ties. Table 1.6 displays the results using the censored values with the preferred specification. The signs and estimates are overall unchanged. This provides confidence that estimated effects are not driven by classes with outlier compositions that may have occurred due to unusual circumstances.

Table 1.7 displays the preferred model with additional control variables of

[17] Recent examples include Dills (2018); Fairlie et al. (2014); Hurtado and Ruiz Alvarado (2015).

classmate shares of students residing in a lower than median income zipcode and females interacted with each corresponding indicator by individual (e.g. ClassmateShare LowerIncome X LowerIcome and ClassmateShare Female X Female). Included are also fixed effects of each category interacted with each course (e.g. Course X LowerIncome and Course X Female). This specification is extremely rich and absorbs identifying variation beyond the standards of literature in peer effects and social interactions.[18] The estimated effects from the preferred specification remain intact, with the Hispanic classmate share still affecting Hispanic students with a decrease in the class drops by a statistically significant 1.1 percentage points.

Although the sequential series of specifications with controls and fixed effects (as displayed on Table 1.3) provide robust evidence for the estimated effects, past and future empirical research on classroom social interactions related to minorities will often require a pooling of minority groups into a single category for statistical power and analysis. In order to provide estimates that are robust and comparable to related studies on minorities, the remaining part of this section provides a discussion on outcomes using the pooled definition of minority. I also leverage the smaller standard errors from pooling to examine alternative robust variations that are less precise.

Table 1.8 displays estimates for the primary outcomes utilizing equation (1.1). This is the same specification as the preferred, with the exception of the pooling of ethnicity and race by the designation of an underrepresented minority category. The estimates show that in aggregate, minority students are 1.1 percentage points less likely

[18]See Sacerdote (2014) for a list of related literature.

to drop a class and 0.7 percentage points more likely enroll in a same subject course the next term for each 10 percentage point increase in share of minority classmates. The other outcomes are statistically insignificant, but show signs in the same direction as the main results. The estimates still display that students are more likely to complete a class with a pass.

Robustness of estimates can also be examined by utilizing departmental term to term variations in minority enrollment compositions. In the spirit of classmate variations, I compute the variation in minority shares within departments and label them as department-mates.[19] Table 1.9 reports these estimates, and also show similar results as with the preferred model. By utilizing department level variations, the estimated effects represent interaction of students within a department, and not necessarily by a classroom. Nonetheless, it appears minorities are also affected in the same manner with department level variations.

1.5.3 Cumulative and Intermediate Outcomes

I also rely on compositional variation of classmates by race and ethnicity to identify effects on number of classes passed and on returning the next term. Since each student can only have one outcome, I replace student fixed effects with course-set by race fixed effects as described in section 1.4.2. Table 1.10 reports both estimates across four specifications. Both Hispanic students and African-American students pass more classes as exposure to similar classmates increase. Column 4 reports the preferred estimates.

[19]This is an adaptation of a strategy made popular in Hoxby (2000) where the researcher examines year to year compositional changes within grade levels at schools.

For Hispanic students I estimate a statistically insignificant increase of 0.006 classes passed. For African-American students I detect an increase in 0.04 classes passed. The base rate for the number of classes passed is 1.96. There appears to be little or no noticeable effect on persistence for Hispanic students. For African-American students, there is a detectable effect of 1.1 percentage points on a sample base rate of 61.9 percent.

1.5.4 Heterogeneity

In this section I examine the students that may be most responsive to the racial and ethnic composition of classmates. I first examine for spillovers that may exist across minority groups. I follow with a specification that displays corroborating results with a seminal experiment on a "sense of belonging" (Walton & Cohen, 2011). Then I examine other characteristics which includes gender, type of coursework, and part-time / full-time enrollment status. To identify differential effects, I include additional interaction terms on minority groups using the preferred specification. This is analogous to the concept of intersectionality in which experiences may be interwoven and heterogeneous between gender, race, and wealth status.

A natural question that arises in this study is the magnitude by which minorities benefit from being in classes with a specific minority race or ethnicity and whether there are any spillovers. Perhaps Hispanic students are more comfortable being in classes with other underrepresented minorities such as African-American students, or vice versa. Alternatively, instructors and non-minority classmates may change their behaviors towards all minorities as a result of changes in either the Hispanic or African-American share of a classroom. To examine if these types of spillover effects exist, Table 1.11 reports regression estimates on interactions between the minority race/ethnicity categories. Each panel corresponds to a single regression. The cells represent the interaction term between the column variable and row variable. Highlighted in bold are the interactions of students between a similar race/ethnicity (This is also the diagonal of each panel.). Although "Other Minority" is included in the regression as a control, it is unreported because this category is combined with multiple underrepresented groups and the sample is small. This table shows that both Hispanic students and African-American students primarily respond to increased compositions of their own race/ethnicity. On both the dropped and passing outcomes, there appears to be little or no spillover in effect across Hispanic and African-American students. The effects are primarily contained within each race/ethnicity.

In Table 1.12, I add an interaction term with a variable indicating a student is White with the classmate share of White students to the preferred model. By including this additional term, it displays a comparison of effects between minority students and White students. This table shows that White students are much less likely to respond to their own racial/ethnic composition in the classroom, while minority groups are still strongly affected by increases in compositions of their own racial and ethnic group. This echoes findings reported by Walton and Cohen (2011). The researchers conducted a "sense of belonging" randomized intervention study and found that African-Americans responded much more favorably to a sense of belonging treatment compared to European-American students. The authors suggest that there may be potential benefits to increasing students' sense of belonging among other marginalized minority groups. The estimates on Table 1.12 suggest that the academic achievement gap for Hispanic students can be addressed in a similar manner.

I start my examination of differential effects with gender in Panel A of Table 1.13. The coefficients of interest are the lower two coefficients in each panel. In this case, the differences in effects between males and females are reported. The only statistically significant differential effects that I detect are on the passing outcome. For this outcome, I detect that African-American females are 3.4 percentage points more likely to pass a class than African-American males as a result of a 10 percentage point increase in African-American classmates. This suggests that classroom compositional changes affect African-American women more than African-American men. Although the other two displayed outcomes do not show statistically significant differential effects for females, they also suggest that African-American females are differentially less likely to drop. African-American men appear to be affected by classroom compositions as well, but the magnitudes are much larger for females.

Socio-economic comparisons may also be relevant, especially for social identity and a sense of belonging. Previous research on social identities (Ostrove & Long, 2007; Oyserman, Johnson, & James, 2011) finds that social-class background has important implications on a student's sense of belonging and are likely to be intertwined with minority-ethnic group memberships. Panel B of Table 1.13 examines the distinction between these potentially interacting effects. For the examination, student zipcodes are linked to median incomes that are made available to the public by the U.S. Census

Bureau. The students are categorized by whether they live in a zipcode that has a median income in the lower 50 percentile of sample or not.[20] This panel displays that Hispanic students from lower income zipcodes are less responsive to classmate racial compositions than their counterparts from higher income zipcodes.

Table 1.14 examines differential effects by enrollment patterns. In Panel A, I examine whether the transferability of a course matters. In this set of outcomes, the only statistically significant coefficient of interest is the differential effect of passing a transferable course relative to a non-transferable course for Hispanic students. The 2.8 percentage point effect shows that Hispanic students are largely affected by ethnic/racial compositions in these competitive courses. A potential explanation for the effect may be increased access to a support network. Competitive and potentially abstract courses often require moral and academic support from peers. Common situations that often require the assistance of peers occur when an instructor rushes through a required curriculum or if an extensive set of background knowledge is required but not discussed during the lecture. The distinct difference between effects on drops and passing suggest that peers are important in competitive environments.

Panel B of Table 1.14 displays differential effects by class enrollment load. Twelve units is the required minimum to be classified as a full time student and each class is generally 4 or 5 units. To closely reflect full time enrollment status, I create an indicator variable to denote students that are enrolled in 2 classes or less. These students are very likely to be part-time students. For the coefficients of interest, only

[20] The average of the median zipcode incomes for Hispanic and African-American students are $69,000 and $67,000 respectively. This compares to an average of $86,000 for non-minority students.

one cell shows statistical significance at the 10% level. The panel reports that part-time Hispanic students are differentially more likely to pass a class than their full-time student counterparts. This highlights that part-time students see a substantial effect in passing a class when they are exposed to classmates with a similar race/ethnicity.

The marginal effects of being underrepresented may be magnified as minorities face an environment with very limited representations (Steele, 2010). To examine this potential mechanism, I generate a indicator variable for minority groups when their representation in a class is below the median in a course's history. Similar to the previous two tables, Table 1.15 reports these differential effects. Although the signs of the differential effects are mixed between Hispanic and African-American students, the only statistically significant differential effect displays that Hispanic students in classes with representations below the median experience a 1.4 percentage points increase in probability of earning credit in addition to the increases their Hispanic counterparts experience. The magnitude of this effect is almost a mirror image of a reduction in drops which is a statistically insignificant 1.2 percentage points.

1.6 Conclusion

The detailed administrative data from an over-subscribed community college provide critical insights into understanding how classroom racial compositions affect the racial achievement gap. By examining first-time college students with limited class choices, I find that minority students are more likely to persist in classes when they are enrolled with classmates of a similar race or ethnicity. This behavior leads to increases in course completions for the term and subsequent enrollment in same subject courses the next term.

Race and ethnicity appear to be distinct for decisions to drop classes with little or no spillovers across minority groups and no detectable heterogeneous effects. The outcome of passing a class to earn credit displays heterogeneous effects. African-American females benefit more than African-American males when they are exposed to more students with a similar race or ethnicity. Hispanic students who are part-time or enroll in UC and CSU transferable courses also experience additional positive effects relative to their Hispanic student counterparts.

The class drop outcome reflect student preferences during their first three weeks of college. These early decisions are likely to be based on projections from previous experiences in social settings. Related studies examining social interactions between instructors (Fairlie et al., 2014) and teaching assistants (Lusher et al., 2018) have also found that students respond favorably to similar races and ethnicities of instructors and teaching assistants.

The policy implications are two fold. First, lack of diversity in post-secondary settings is likely to perpetuate achievement gaps and sorting across course subjects for underrepresented minorities. Second, in instances where minority representations are limited, institutions may provide a better environment for minority students by increasing opportunities to opt into classrooms and/or learning communities where they are not marginalized. Many post-secondary institutions already implement similar policies with community based practices and it appears that it is fruitful to incorporate them close to or into classrooms.[21]

For most individuals, race and ethnicity is not a choice. Instead they must choose between social environments to fit in. In this crucial setting with long-term economic consequences, minority students demonstrate that classmate racial composition matter by exhibiting increases in class passing, subject persistence, and institutional persistence.

[21]For example, UC Santa Cruz allows students to select from one of ten thematic colleges which provide unique curriculum and residential accommodations. Alternatively, Stanford offers students the opportunity to apply to ethnic themed housing focused on histories and cultures.

Figure 1.1: Distribution of Class Enrollment

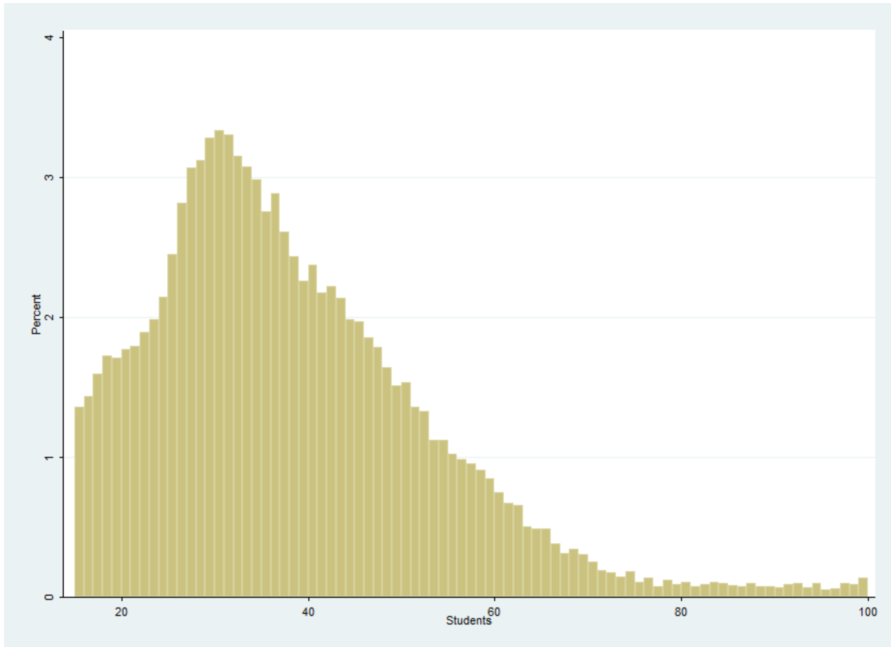
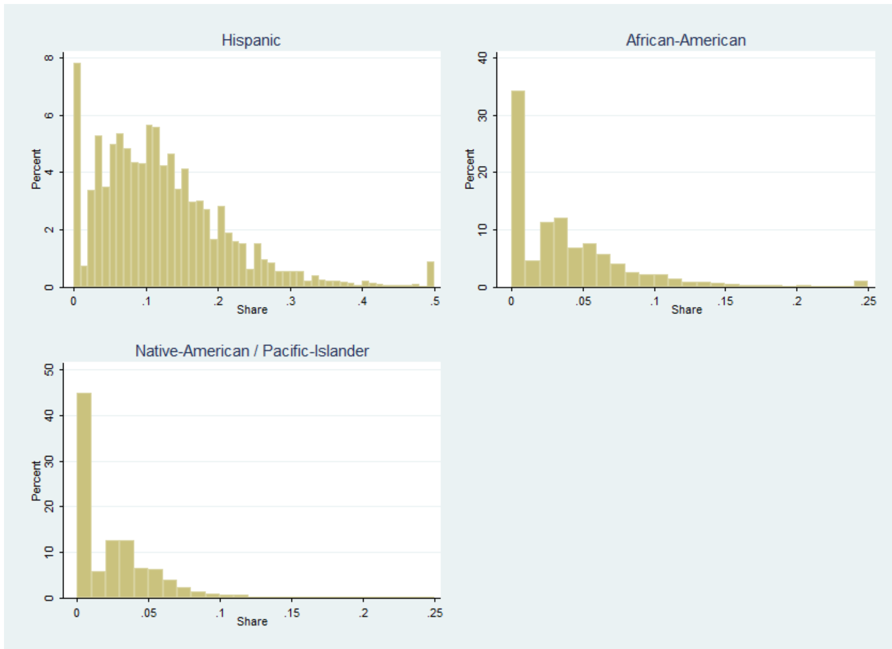


Figure 1.2: Distribution of Class Composition



Note: Ethnicity/race are right censored.

Table 1.1: Descriptive Statistics

Panel A: Student Characteristics

	Mean	SD
White	0.278	0.448
Asian	0.460	0.498
Hispanic	0.173	0.378
African-American	0.060	0.237
Other Minority	0.030	0.169
Female	0.499	0.500
Age	23.806	8.556
Zipcode Median Income	81,652	23,618
Observations	*186,336*	

Panel B: Student Outcomes By Race/Ethnicity

	White		Asian		Hispanic		African-American		Other-Minority	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Short-Term Outcomes										
Dropped	0.170	0.376	0.179	0.383	0.157	0.363	0.192	0.394	0.196	0.397
Withdraw	0.118	0.322	0.094	0.292	0.127	0.333	0.126	0.332	0.133	0.340
Passed (Unconditional on Drop or Withdraw)	0.637	0.481	0.659	0.474	0.581	0.493	0.548	0.498	0.574	0.494
Passed (Conditional)	0.873	0.333	0.889	0.315	0.792	0.406	0.780	0.414	0.826	0.379
Grade Points (Conditional)	3.007	1.248	3.050	1.197	2.491	1.302	2.370	1.265	2.712	1.330
Cumulative / Intermediate Outcomes										
Number of Classes Passed During First-Term	1.846	1.537	2.112	1.555	1.727	1.525	1.666	1.532	1.868	1.572
Takes Same Subject Next Term	0.255	0.436	0.287	0.452	0.318	0.466	0.365	0.481	0.25	0.433
Returns Next Term	0.568	0.495	0.636	0.481	0.619	0.486	0.615	0.487	0.608	0.488
Observations	*51,712*		*85,762*		*32,194*		*11,169*		*5,499*	

Panel C: Summary Characteristic of Classes

	Mean	SD
Enrollment	37.842	14.879
Share of Students: First-Time	0.172	0.157
Share of Students: Under-Represented Minority	0.186	0.113
Share of Students: Hispanic	0.123	0.091
Share of Students: African-American	0.039	0.046
Share of Students: Other-Minority	0.024	0.029
Classes	*32,867*	

Notes: Other minority indicates that a student is Native-American or Pacific-Islander. An A is equivalent of a 4.0 in grade points.

Table 1.2: Tests For Sorting Into Classrooms

VARIABLES	Class Enrollment Size (1)	Female (2)	Ln(age) (3)	Median Income By Zipcode (4)	Female (5)	Ln(age) (6)	Median Income By Zipcode (7)
Hispanic X Classmate Share Hispanic	-2.959	0.054	-0.010	-8,886.942	0.031	-0.006	127.392
	(3.288)	(0.061)	(0.038)	(6,767.933)	(0.043)	(0.023)	(2,338.499)
African-American X Classmate Share A.A.	-4.861	-0.081	-0.025	2,073.861	-0.080	-0.025	1,308.981
	(3.271)	(0.080)	(0.039)	(4,712.943)	(0.076)	(0.029)	(1,958.585)
Observations	185,178	184,920	185,121	178,810	177,642	177,847	171,446
Fixed Effects							
Class					X	X	X

Notes: This table displays results from the sorting regressions. Included in the regressions are term and course by race fixed effects. The coefficient on the interaction of other minorities (Native-American / Pacific-Islanders) with similar classmates are not reported. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.3: Estimated Effect of Classmates On Course Related Outcomes

	(1)	(2)	(3)	(4)	(5)
Dropped Course					
Hispanic X Classmate Share Hispanic	-0.104**	-0.107**	-0.128***	-0.131***	-0.126***
	(0.045)	(0.045)	(0.044)	(0.047)	(0.046)
African-American X Classmate Share A.A.	-0.036	-0.014	-0.198*	-0.253*	-0.252*
	(0.043)	(0.047)	(0.105)	(0.132)	(0.128)
Dropped or Withdrew					
Hispanic X Classmate Share Hispanic	-0.156***	-0.114**	-0.109***	-0.096***	-0.092***
	(0.051)	(0.052)	(0.039)	(0.033)	(0.033)
African-American X Classmate Share A.A.	-0.050	-0.029	-0.298**	-0.283	-0.276
	(0.063)	(0.058)	(0.121)	(0.179)	(0.178)
Passed Course (Unconditionally)					
Hispanic X Classmate Share Hispanic	0.200***	0.105*	0.157***	0.122*	0.116*
	(0.055)	(0.055)	(0.051)	(0.064)	(0.062)
African-American X Classmate Share A.A.	0.305***	0.150***	0.290***	0.185	0.170
	(0.091)	(0.050)	(0.091)	(0.177)	(0.174)
Takes Course in Same Subject Next Term					
Hispanic X Classmate Share Hispanic	0.201***	0.073**	0.093	0.098**	0.092**
	(0.048)	(0.027)	(0.067)	(0.043)	(0.045)
African-American X Classmate Share A.A.	0.229**	0.070	0.153	0.065	0.075
	(0.093)	(0.058)	(0.130)	(0.159)	(0.157)
Observations	184,485	177,188	149,057	137,806	137,806
Controls					
Student	X	X			
Class	X		X		
Fixed Effects					
Term	X				
Class		X		X	X
Student			X	X	X
Race X Instructor Race					X

Notes: This table displays results from the main outcome regressions. Controls for students include gender, international student status, zipcode, and quadratic polynomial of age. Controls for classrooms include the classmate share by each respective minority race/ethnicity. The coefficient on the interaction of other minorities (Native-American / Pacific-Islanders) with similar classmates are not reported. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.4: Estimated Effect of Classmates (Conditional On Returning Next Term)

	(1)	(2)	(3)	(4)	(5)
Takes Course in Same Subject Next Term					
Hispanic X Classmate Share Hispanic	0.221***	0.079*	0.116	0.095*	0.085
	(0.063)	(0.040)	(0.075)	(0.054)	(0.056)
African-American X Classmate Share A.A.	-0.012	-0.002	0.204	0.062	0.084
	(0.055)	(0.044)	(0.179)	(0.204)	(0.192)
Observations	112,549	104,254	100,809	89,126	89,126
Controls					
Student	X	X			
Class	X		X		
Fixed Effects					
Term	X				
Class		X		X	X
Student			X	X	X
Race X Instructor Race					X

Notes: This table displays results from the main outcome regressions. All specifications include course by race fixed effects. Controls for students include gender, zipcode, and quadratic polynomial of age. Controls for classrooms include the classmate share by each respective minority race/ethnicity. The coefficient on the interaction of other minorities (Native-American / Pacific-Islanders) with similar classmates are not reported. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.5: Estimated Effects of Minority Classmates Who Are Also First-Time

	Dropped	Dropped or Withdrew	Passed-Unconditional	Takes Same Subject Next Term
	(1)	(2)	(3)	(4)
Hispanic X Classmate Share Hispanic (First-Time)	-0.172**	-0.080	0.183**	0.140*
	(0.076)	(0.071)	(0.081)	(0.069)
African-American X Classmate Share A.A. (First-Time)	-0.256*	-0.248	0.144	0.282
	(0.138)	(0.164)	(0.182)	(0.171)
Observations	137,806	137,806	137,806	137,806

Notes: This table displays results from the main outcome regressions. The classmate share in these regressions represent the share of students who are first-time and minority. The denominators of the share values are calculated from all classmates. The results are also similar when the denominator is constructed with first-time students. Course by race, class, and student fixed effects are included in all regressions. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.6: Estimated Effect of Classmates (Winsorized By .05)

	Dropped	Dropped or Withdrew	Passed-Unconditional	Takes Same Subject Next Term
VARIABLES	(1)	(2)	(3)	(4)
Hispanic X Classmate Share Hispanic (W .05)	-0.132**	-0.085**	0.103	0.095*
	(0.054)	(0.034)	(0.067)	(0.051)
African-American X Classmate Share A.A. (W .05)	-0.393*	-0.603**	0.416	0.048
	(0.195)	(0.249)	(0.247)	(0.204)
Observations	137,806	137,806	137,806	137,806

Notes: This table displays results from the main outcome regressions with the share of classmates ethnicity winsored at the 5% level. Course by race, class, and student fixed effects are included in all regressions. The coefficient on the interaction of other minorities (Native American / Pacific Islanders) with similar classmates are not reported. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.7: Estimated Effect of Classmates (Including Interactions With Other Demographic Shares)

VARIABLES	Dropped (1)	Dropped or Withdrew (2)	Passed-Unconditional (3)	Takes Same Subject Next Term (4)
Hispanic X Classmate Share Hispanic	-0.110**	-0.073**	0.094	0.079
	(0.046)	(0.034)	(0.066)	(0.047)
African-American X Classmate Share A.A.	-0.233	-0.317	0.141	0.025
	(0.139)	(0.195)	(0.192)	(0.158)
Observations	131,860	131,860	131,860	131,860

Notes: This table displays results from the main outcome regressions using the preferred model with the addition of interaction terms on classmate share by an indicator for residence at a zipcode with income below the median, and gender. The fixed effects include student, class, course by race, course by lower income zipcode, and course by female. The coefficient on the interaction of other minorities (Native-American / Pacific-Islanders) with similar classmates are not reported. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.8: Estimated Effects of Minority Classmates

	Dropped (1)	Dropped or Withdrew (2)	Passed-Unconditional (3)	Takes Same Subject Next Term (4)
Minority X Classmate Share Minority	-0.111***	-0.066	0.090	0.073**
	(0.039)	(0.045)	(0.058)	(0.032)
Observations	137,806	137,806	137,806	137,806

Notes: This table displays results from the main outcome regressions that correspond to equation 1. Course by race, class, and student fixed effects are included in all regressions. The classmate share variable is constructed from the share of classmates who are minorities. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.9: Estimated Effects of Minority Department-Mate

	Dropped	Dropped or Withdrew	Passed-Unconditional	Takes Same Subject Next Term
	(1)	(2)	(3)	(4)
Minority X Department-mate Share Minority	-0.278	-0.294	0.441**	0.459***
	(0.216)	(0.267)	(0.178)	(0.145)
Observations	137,806	137,806	137,806	137,806

Notes: This table displays results from the main outcome regressions similar to equation 1. Course by race, class, and student fixed effects are included in all regressions. The department-mate share minority variable is constructed from the share of department-mates who are minority during the term. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.10: Estimated Effect of Classmates on Cumulative and Intermediate Outcomes

	(1)	(2)	(3)	(4)
Number of Classes Passed				
Hispanic X Classmate Share Hispanic	0.119	0.092	0.158*	0.057
	(0.164)	(0.171)	(0.090)	(0.149)
African-American X Classmate Share A.A.	0.565***	0.532***	0.273	0.404**
	(0.173)	(0.172)	(0.227)	(0.196)
Returns Next Term				
Hispanic X Classmate Share Hispanic	0.026	0.007	-0.021	-0.004
	(0.058)	(0.057)	(0.041)	(0.053)
African-American X Classmate Share A.A.	0.146***	0.149***	0.066	0.111*
	(0.045)	(0.053)	(0.054)	(0.057)
Observations	177,903	177,188	178,182	176,977
Student Controls		X	X	X
Fixed Effects				
Course X Race	X	X		X
Number of Courses Enrolled X Race	X	X		
Course Set X Race			X	X

Notes: This table displays results from the cumulative outcomes model. All estimates include class fixed effects. Controls for students include gender, quadratic polynomial of age, and indicators for zipcode. Controls for classrooms include the classmate share by each respective minority race/ethnicity. Course set are unique indicators for combination of courses students take in the first term. The coefficient on the interaction of other minorities (Native American / Pacific Islanders) with similar classmates are not reported. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.11: Estimated Effects of Classmates and Spillovers

	Hispanic	African-American
Panel A: Dropped		
Classmate Share Hispanic	**-0.098*** **	0.013
	(0.036)	(0.146)
Classmate Share African-American	0.032	**-0.285**
	(0.109)	**(0.194)**
Panel B: Passed (Unconditional)		
Classmate Share Hispanic	**0.124***	-0.068
	(0.068)	(0.134)
Classmate Share African-American	0.032	**0.220**
	(0.105)	**(0.192)**
Panel C: Takes Same Subject Next Term		
Classmate Share Hispanic	**0.103****	-0.033
	(0.046)	(0.078)
Classmate Share African-American	0.121	**0.104**
	(0.106)	**(0.171)**
137,806 Observations		

Notes: The table displays coefficients from a regression fully interacting each minority groups (columns) with corresponding classmate groups (rows). Interactions with "Other Minorities" and other minority classmates are included in the regression but are not reported. Each panel is composed of coefficients from a single corresponding regression. Similar to the preferred specification, the regressions in panel A and panel B include student, class, and course by race fixed effects. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.12: Including White Student Interactions

	Dropped	Passed-Unconditional	Takes Same Subject Next Term
	(1)	(2)	(3)
Hispanic X Classmate Share Hispanic	-0.127***	0.118*	0.101**
	(0.046)	(0.062)	(0.042)
African-American X Classmate Share A.A.	-0.249*	0.182	0.067
	(0.132)	(0.178)	(0.160)
White X Classmate Share White	-0.049	0.039	-0.033
	(0.045)	(0.036)	(0.037)
Observations	137,806	137,806	137,806

Notes: This table displays results from the main outcome regressions using the preferred model with the addition of the interaction term between an indicator for a White student with shares of White classmates. Course by race, class, and student fixed effects are included in all regressions. The coefficient on the interaction of other minorities (Native-American / Pacific-Islanders) with similar classmates are not reported. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.13: Heterogeneous Effects By Student Characteristic

	Dropped	Passed-Unconditional	Takes Same Subject Next Term
	(1)	(2)	(3)
Panel A: By Gender			
Hispanic X Classmate Share Hispanic	-0.119**	0.114*	0.132**
	(0.047)	(0.061)	(0.050)
African-American X Classmate Share A.A.	-0.193	0.048	-0.016
	(0.143)	(0.195)	(0.180)
Hispanic X Classmate Share Hispanic X Female	-0.022	0.013	-0.066
	(0.037)	(0.049)	(0.059)
African-American X Classmate Share A.A. X Female	-0.146	0.336**	0.194
	(0.135)	(0.145)	(0.138)
Panel B: By Median Income of Zipcode			
Hispanic X Classmate Share Hispanic	-0.072	0.143*	0.210**
	(0.058)	(0.084)	(0.079)
African-American X Classmate Share A.A.	-0.407	0.065	0.179
	(0.314)	(0.249)	(0.234)
Hispanic X Classmate Share Hispanic X Lower Income Zip	-0.028	-0.031	-0.094**
	(0.055)	(0.080)	(0.046)
African-American X Classmate Share A.A. X Lower Income Zip	0.130	0.064	-0.097
	(0.162)	(0.110)	(0.124)
Observations	137,806	137,806	137,806

Notes: This table displays results from the main outcome regressions using the preferred model with the addition of interaction terms as specified by the panel to the three minority groups. Course by race, class, and student fixed effects are included in all regressions. The coefficient on the interaction of other minorities (Native-American/Pacific-Islanders) with similar classmates are not reported. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.14: Heterogeneous Effects By Enrollment Pattern

	Dropped	Passed-Unconditional	Takes Same Subject Next Term
	(1)	(2)	(3)
Panel A: By CSU/UC Transferable Course			
Hispanic X Classmate Share Hispanic	-0.105	-0.031	0.030
	(0.072)	(0.074)	(0.088)
African-American X Classmate Share A.A.	-0.603**	0.376*	-0.255
	(0.271)	(0.213)	(0.276)
Hispanic X Classmate Share Hispanic X Transferable	-0.048	0.275***	0.121
	(0.100)	(0.098)	(0.107)
African-American X Classmate Share A.A. X Transferable	0.476	-0.268	0.431*
	(0.400)	(0.272)	(0.245)
Panel B: By Number of Courses Enrolled (Less Than 3)			
Hispanic X Classmate Share Hispanic	-0.136***	0.099	0.086*
	(0.048)	(0.065)	(0.044)
African-American X Classmate Share A.A.	-0.293*	0.219	0.088
	(0.145)	(0.181)	(0.167)
Hispanic X Classmate Share Hispanic X Enroll Less	0.043	0.190*	0.097
	(0.099)	(0.112)	(0.075)
African-American X Classmate Share A.A. X Enroll Less	0.314	-0.257	-0.181
	(0.201)	(0.206)	(0.135)
Observations	137,806	137,806	137,806
Fixed Effects			

Notes: This table displays results from the main outcome regressions using the preferred model with the addition of interaction terms as specified by the panel to the three minority groups. Course by race, class, and student fixed effects are included in all regressions. The coefficients on the interaction of other minorities (Native-American/Pacific-Islanders) with similar classmates are not reported. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 1.15: Hetereogenous Effects By Levels of Representation

	Dropped	Passed-Unconditional	Takes Same Subject Next Term
	(1)	(2)	(3)
Hispanic X Classmate Share Hispanic	-0.169***	0.168**	0.121***
	(0.049)	(0.072)	(0.036)
African-American X Classmate Share A.A.	-0.245	0.168	0.053
	(0.156)	(0.190)	(0.156)
Hispanic X Classmate Share Hispanic X Low Rep	-0.113	0.139*	0.074
	(0.071)	(0.075)	(0.055)
African-American X Classmate Share A.A. X Low Rep	0.078	-0.130	-0.104
	(0.185)	(0.184)	(0.123)
Observations	137,806	137,806	137,806

Notes: This table displays results from the main outcome regressions using the preferred model with the addition of an interaction variable that indicates that the class has representation below the observed median share within a course for the corresponding minority group. Course by race, class, and student fixed effects are included in all regressions. The coefficients on the interaction of other minorities (Native-American / Pacific-Islanders) with similar classmates are not reported. Standard errors are in parentheses clustered at the course and term level. One, two, and three asterisks indicate statistical significance at 10, 5, and 1% levels, respectively.

Chapter 2

A New Generation of Female Scientists? Gender Interactions in Gateway Chemistry Labs

2.1 Introduction

The underrepresentation of women in STEM fields is one of the most pressing problems in higher education. The disparity exists around the world and contributes substantially to gender earnings inequality because STEM jobs are typically high paying (Beede et al., 2011; Card & Payne, 2017; Weinberger, 1999; Shen, 2013). Although numerous explanations for these disparities have been studied, of particular concern is that the lack of role models, stereotype threat, gender bias, and fear of competition contribute to fewer women taking courses and graduating in STEM fields (Corbett & Hill, 2015; Spencer, Steele, & Quinn, 1999; Carrell et al., 2010; Niederle & Vesterlund, 2010;

Solanki & Xu, 2018; Avilova & Goldin, 2018; Leslie, Cimpian, Meyer, & Freeland, 2015; Rask & Tiefenthaler, 2008; Moss-Racusin, Dovidio, Brescoll, Graham, & Handelsman, 2012; Woodcock & Bairaktarova, 2015).

All of these negative influences might be heightened when female students interact frequently with male students in STEM fields. For example, female college students in STEM report high levels of gender bias from male peers (Robnett, 2016) and often report leaving STEM because of a negative climate characterized by intense competition, lack of support, and discouraging peers (Goodman, 2002). Female students are also found to be negatively affected by competitive environments in STEM classes whereas male students are not affected (Fischer, 2017). These concerns at least partly underlie interest in and arguments for same-sex schools or programs, even though the evidence is mixed on their effectiveness (Halpern et al., 2011; Mael, Alonso, Gibson, Rogers, & Smith, 2005; McCartney, 2016).

To explore these concerns, we conduct the first-ever large-scale experiment of interactions between female and male students in Chemistry. Similar to most other STEM fields female students are severely underrepresented in Chemistry (Snyder, De Brey, & Dillow, 2018; NCES, 2018). For the experiment, students in every lab section associated with the first-year sequence in Chemistry at a large public research university are randomly assigned a partner. The study involves 3,902 students over four academic years (total N=5,537). The experiment specifically tests whether the academic outcomes of female college students are negatively affected by being paired with male students, and whether those interactions depend on the students ability, partners ability, how many other women are in the lab section, and whether they have a female graduate student teaching assistant.

Randomly assigning students to lab partnerships allows us to avoid the common estimation bias resulting from self-selection (i.e. students might choose to work with their friends, other students like themselves, or students who can help them the most) and several additional statistical limitations. Chemistry labs provide an ideal setting in which to study gender interactions because students work in pairs that are assigned for the entire term. In a classroom of 300 students, or even 30 students, it is very difficult to identify which classmates have the most influence on a particular student.[1] In Chemistry labs, students work very closely together but take individual assessments and are graded on their own knowledge of the subject material. The one-to-one matching in Chemistry labs removes this measurement problem and provides an intensive interaction between students.

The Introduction to Chemistry sequence which includes the labs is the gateway requirement to a diverse set of STEM majors, including Chemistry, Biology, Bioengineering, Environmental Studies, Environmental Science, Earth Sciences, Ecology and Neuroscience. It is also commonly taken by students in many other STEM majors (e.g. Physics, Computer Science, and Cognitive Science). Chemistry labs develop a broad skillset including a strong mathematical component (e.g. statistics, linear regression, physical processes, experimental measurement, and instrumentation). Overall, Chemistry labs provide an ideal and important setting to test whether female students

[1] Additionally, we avoid the concern that random assignment creates little, or essentially no, variation in female shares of classrooms (Angrist, 2014). Lab pairs are either 0% female or 100% female.

experience negative interaction effects from male students early in their in their STEM college experience when they are especially vulnerable to switching majors (Goodman, 2002).

2.2 Setting

At a large, public university, we randomized all student pairings in introductory Chemistry labs starting in Winter Quarter 2015. The University has a total enrollment of nearly 20,000 students. The Chemistry labs are associated with the introductory courses required in Chemistry. The total enrollment in all labs observed for our study is 5,537, the average enrollment in each introductory Chemistry course is 348, and enrollment in the 330 Chemistry labs is capped at 18 (mean=16.8).

The Introduction to Chemistry sequence at the university covers a standard set of topics, similar to other large research universities. The laboratory classes associated with this sequence are also standard. The sequence requires a minimum of pre-calculus before enrolling, but most students have already taken calculus. The sequence involves extensive use of math throughout the coursework. Students generally take Chem 1A, 1B and 1C in consecutive quarters. The two labs (Chem 1M and 1N) are associated with the second and third quarter courses in the sequence, respectively.

Chemistry labs are taken by students from a diverse set of majors across campus. The introductory Chemistry sequence is required for most science majors, and students have large representations from Chemistry, Biology, Bio-Engineering, Neuroscience, Computer Science, Ecology, and Psychology. The laboratory curriculum, physical equipment and space are standardized across sections. The laboratory equipment and materials are uniformly disbursed from a central laboratories manager. Lab sections are held in eight different laboratory classrooms along one hallway in the Chemistry instruction building. The standardization across lab sections provides one of the most controlled environments for studying social interactions between students possible on a college campus.

At both the undergraduate and graduate level, women are underrepresented in Chemistry, which is similar to most other STEM fields. Nationally, women receive 48 percent of Chemistry bachelors degrees compared to 57 percent of all bachelors degrees (Snyder et al., 2018). Women also receive only 37 percent of doctorates in Chemistry and this percentage has remained unchanged over the past decade (NCES, 2018). At the university, 42 percent of Chemistry majors are female, and 38 percent of graduate students in Chemistry are female.

2.3 Methods

To study peer effects between female and male students in Chemistry labs we randomly assigned students to work together. Partners in all introductory Chemistry lab courses over the past four years were randomly assigned on the first day of their section. These partnerships were maintained for the entire term. The process of randomization is deliberately transparent. Students draw folded slips of paper with numbers between

1 and 9 from a large beaker. Students with matching numbers are paired. When only 16 students (or an even amount of students below 18) are present for the draw, pairs of slips with the same number are either omitted from the beaker, or students with the lowest unmatched numbers are matched. When only 17 students (or an odd number of students) are present for the draw, the non-matching student is added to the lowest numbered pair. We drop these observations which represent only 2 percent of the partnerships. To check statistical validity, we perform a balance check of randomization in our experiment. As expected with random assignment of lab partners we find that students paired with female students are observably similar to students paired with male students. Table 2.1 reports detailed demographic and academic characteristics of both groups of students and confirms that in all cases there are no statistically significant differences between the two groups. To test the effects of female students interacting with male students in Chemistry lab pairings we estimate the following equation.

$$Y_i = \beta_1 X_i + \beta_2 F_i + \beta_3 F_i \times M_i^{PT} + \beta_4 M_i \times F_i^{PT} + \gamma_s + \epsilon_{is} \tag{2.1}$$

where Y_i is the student's academic outcome, X_i is a vector of background characteristics of the student, $F_i = 1$ if the student is female, $M_i = 1$ if the student is male, $F_i^{PT} = 1$ if the students partner is female, $M_i^{PT} = 1$ if the students partner is male, γ_s are unique lab section fixed effects, and ϵ_{is} is the error term. β_2 captures the performance difference between female and male students, all else equal. β_3 captures the effect of female students being partnered with male students relative to being partnered with female students. The coefficient estimate will be negative if female students perform worse when matched with male lab partners. β_4 captures whether male students are affected by being partnered with a female student relative to being partnered with a male student. The coefficient estimate provides some evidence on whether female partners negatively affect male students. It also provides evidence on whether there is symmetry in gender interaction effects.

It is important to note that the inclusion of lab section fixed effects in Equation (2.1) controls for the variation in performance due to different instructors, teaching assistants, rooms, lab courses (i.e. Chemistry 1M and 1N), academic years/terms, section times, and days of the week. Importantly, it also implicitly controls for the female/male mix of all students in the lab. The inclusion of lab section fixed effects makes it unnecessary, and in fact mathematically impossible, to include measures of these non-student characteristics in the equation.

2.4 Results

We first examine the performance of female and male students in Chemistry labs. We rescale the underlying numeric continuous score (i.e. scale of 0-100) in the course by demeaning and dividing by the standard deviation.[2] Female students perform modestly better than male students. The mean and median differences between female and male students are 0.275 and 0.208 standard deviations, respectively. The female median lies in the 59th percentile of the male distribution.

[2]Final scores in the class are based on the following assignments: Written procedure and data tables (7) 25%; Online prelabs (7) 5%; Online in-lab assignments (7) 35%; Online reviews (7) 5%; Formal abstracts (2) 10%; Online quizzes (7) 10%; Scholarship and week 1 worksheet 10%.

Turning to the educational effects of female/male interactions in Chemistry labs, Table 2.2 reports estimates of Equation (2.1). We first discuss estimates for the numeric continuous score in the lab course which are reported in Specification 1.[3] Female students do no worse when partnered with a male student than when partnered with a female student. We find a coefficient estimate on β_3 that is essentially zero and is estimated very precisely. The point estimate is 0.00377 and the 95 percent confidence interval is [-0.0625, 0.0700], which rules out even small negative or positive effects on scores in the course. Although female college students in STEM report high levels of experiencing gender bias from male peers on surveys (Robnett, 2016) we do not find evidence that male partners negatively affect their performance. The third key finding from Table 2.2 is that male students are also not affected by having female partners.

We find similar results when we examine additional measures of performance in the Chemistry lab course. Specification 2 reports estimates in which the dependent variable is the grade in the course on a 4-point scale (i.e. scaled similarly as a GPA measure, 0-4.3), and Specification 3 reports estimates for whether the student passed the course.[4] Using both alternative measures of course performance, female students are unaffected by being partnered with male students.[5]

Gender interactions in STEM fields might operate along different channels than

[3] We examine the correlation in course scores between partners. Because grades are determined independently based on quizzes, assignments and prelabs the correlation is not strong 0.06.

[4] Specifications 3 and 4 are estimated with OLS. We find similar estimates for marginal effects when estimating Probit or Logit models.

[5] The estimates are robust to excluding controls for student characteristics, which is expected because of the random assignment of male and female partners. We also find similar results for specifications that add a control for partners performance in Chem 1A and find no effect of this variable. Previous research finds that female students are negatively affected in STEM by higher ability peers whereas male students are not affected (Fischer, 2017).

course performance. For example, female students might decide to drop Chemistry labs when randomly assigned to a male partner before a score or grade is recorded in the system. Dropping the course could have subsequent consequences such as disrupting the students trajectory in the major or even causing the student to lose interest in STEM. Specification 4 reports estimates of Equation (2.1) in which the dependent variable is whether the student dropped the course. These results are important because they shed light on behavioral responses to partnerships. We find that female students are not more likely to drop the lab course when they are partnered with a male student. Symmetrically, male students are also not more likely to drop the course when partnered with a female student.

2.4.1 Related STEM Outcomes

Although male partners do not appear to affect the performance of female students in the lab course, they might affect interest in continuing in Chemistry or STEM more generally. Table 2.3 reports estimates of Equation (2.1) for additional outcomes. First, we examine whether male partners negatively influence subsequent course taking in Chemistry and STEM courses by female students. Specification (1) reports estimates of gender interactions when the dependent variable is future enrollment in the secondary sequence in organic chemistry. Specification (2) switches the focus to declaring majors in Chemistry, and Specification (3) explores declaring majors in any STEM field. Specification (4) explores the impacts on grades in the large lecture Chemistry courses taken concurrently with the lab. For all of these measures of longerterm interest in continuing in STEM, we do not find evidence that female students are negatively affected when partnered with male students.

2.4.2 Performance in Chemistry 1A

Chemistry 1A is the first course in the Introduction to Chemistry sequence. Female students who do well in this course might react differently to peer effects of male students in the labs. For example, receiving a good grade in Chem 1A might reduce the potential for stereotype threat, or causes a student to shy away from competition because they already proved that that they can do well in a competitive environment.[6] On the other hand obtaining a lower grade in Chem 1A might magnify these concerns and increase dissatisfaction reducing interest in STEM (Goodman, 2002). Using grades in Chemistry 1A (which is taken prior to the labs) we examine separate estimates of being partnered with male students for students obtaining a B grade or higher (which represents the top 46 percent of the distribution) or a B- grade or lower.[7] Although on average female students do not appear to be affected by being partnered with male students there could be offsetting negative and positive effects for female students based on performance in Chemistry 1A.

Table 2.4 reports regression estimates for the same four course outcomes as reported in Table 2.2 but now includes interaction terms for low and high ability students

[6] Chemistry 1A is a difficult and competitive course. The grade in this course factors into whether students are accepted into the selective Chemistry major. In Chemistry 1A, 13 percent of students receive Fs and another 6 percent receive Ds. Only 23 percent of the class receives a grade of A- or higher.

[7] The results are not sensitive to when we used alternative cutoffs such as B+ or higher (32 percent of the distribution) or B- or higher (56 percent of the distribution) to define the higher-ability group.

based on performance in Chemistry 1A. We find that both low and high ability female students are not affected by male partners in Chemistry labs. We also find symmetrically that there is no evidence suggesting that low or high ability male students are affected when partnered with female students relative to being partnered with male students.

The ability level of the partner might also affect the gender interaction. If female students are partnered with male students of high ability then it might increase the potential for stereotype threat, fear of competition or discrimination. On the other hand, female students who are partnered with low ability male students might not face these negative influences or, alternatively, may perform down to the level of the low ability male partner. The null effect estimated above (i.e. Table 2.2) might simply represent offsetting negative and positive effects. We examine separate estimates of peer effects by whether the partner was high ability (i.e. B or higher in Chemistry 1A) or low ability (i.e. B- or lower in Chemistry 1A). Table 2.5 reports regression estimates for the four course outcome measures but now includes interaction terms with low and high ability partners. We find no evidence that the partners ability level matters. Female students are not affected when paired with a low ability male student or when paired with a high ability male student. Similarly, male students are unaffected by the ability level of female partners.

As a robustness check, we also distinguish between low and high ability based on a students performance in all previous courses (i.e. prior GPA). We use the median prior GPA for all students to define the low vs. high ability cutoff which is 3.21. Similar to the results using Chemistry 1A as the measure of ability, we find that low-ability female students are not affected by male partners in Chemistry labs (see Table 2.6). High ability female students are also not affected by male partners. Using prior GPA to define low and high ability partners also does not change the results (see Table 2.7). Female students are not negatively affected by either high ability male partners or low ability male partners.

2.4.3 Presence of Other Female Students in Lab

If gender bias is stronger in STEM classes with a relatively high percentage of male students then we might find negative effects of being partnered with males in those classes. We explore whether the share of female students in the lab interacts with having a male partner. Table 2.8 reports regression estimates for the four course outcome measures including interaction terms for high (majority) or low (non-majority) female shares of students in the lab. We find that having a male partner in labs with either high or low female shares has no effect on female students. For male students, we also find no interaction effect with the share of female students in the lab.

2.4.4 Presence of Female Graduate Student Teaching Assistants

The importance of role models in education has been well documented in the literature (Carrell et al., 2010; Solanki & Xu, 2018; Porter, Serra, et al., 2017). Although variation in faculty teaching large introductory Chemistry courses is limited to only five different professors over the past four years, there is substantial variation in the graduate student teaching assistants who run the Chemistry labs. Of the 71 different teaching assistants running labs, 45 percent were women. The presence of a female role model as a PhD student teaching assistant could offset or negate any potential negative effects of male partners on female students. Furthermore, having a female teaching assistant could reduce stereotype threat because of the salient signal of success and ability of women in Chemistry (through the PhD student serving as a TA), and reduce potential discrimination against female students.

Using administrative data on the gender of teaching assistants in each lab, we estimate male partner effects based on the gender of the teaching assistant assigned to the section. Table 2.9 reports regression estimates for the four course outcome measures including interaction terms for teaching assistant assignments.[8] We find that in labs with both female and male teaching assistants having a male partner has no effect (negative or positive) on female students. In environments with and without TA role models and different potential levels of stereotype threat we find no evidence that female students are affected by male lab partners.

2.5 Conclusion

Using the first-ever experiment that randomly pairs female and male students in introductory Chemistry labs at a large public research university, we explore gender interactions in STEM. The findings are surprising. Although students work very closely the entire term in Chemistry labs, we find no evidence that female students are

[8] Importantly, the gender of the teaching assistant is revealed prior to when lab partners are randomly assigned. Furthermore, teaching assistant assignments to labs are not known to students prior to when enrolling in labs.

negatively affected by male students. Female students do no worse when paired with male students than when paired with female students. Female students do not receive lower scores or grades, and they are no more likely to drop the course, or lose interest in continuing in a STEM field. These findings are likely quite broad and not related to any specific set of scientific concepts or skills given the broad range of capabilities required in introductory chemistry laboratories.

The new generation of female college students might face less gender bias and stereotype threat in STEM, eliminating potential negative effects by male lab partners. Female students are also generally doing better in gateway Chemistry labs than male students providing evidence that ability differences are not the root cause of gender differences in STEM majors. Furthermore, the lack of a negative reaction to male partners suggests that female students in Chemistry might be facing declining gender bias from male peers (Robnett, 2016).

Diving deeper into additional interactions with student ability we find no evidence suggesting that academically weaker female students are negatively affected by male students and no evidence that female students are negatively affected when paired with academically stronger male students (both of which might suggest strong stereotype and competition threats to female students). The presence of a female role model, represented by a PhD student teaching assistant running the lab, also does not alter the effects of the interaction with male students.

Although concerns continue over the underrepresentation of women in STEM fields, the future might be brighter if the new generation of female students is not negatively affected by male peers in male-dominated STEM fields. Perhaps, one of the most fruitful future directions for increasing female participation in STEM is to focus on increasing interest in STEM fields in high school and college by emphasizing the salience of jobs in these fields for solving broader world problems (Card & Payne, 2017; Corbett & Hill, 2015; Avilova & Goldin, 2018; Levine, Serio, Radaram, Chaudhuri, & Talbert, 2015). Even so, systemic change will require strong and continuing support at all levels of education by university leaders, policymakers and others (Handelsman et al., 2005; NSF, 2018). But the stakes are high and worth the investment as increasing women in STEM is likely to reduce earnings inequality and represents a vast resource for economic growth in countries where female labor participation has been historically low (Hanushek, 2008).

Table 2.1: Balance - Mean Student Characteristics by Partner's Gender

	Female Partner	Male Partner	Difference	(P-Value)
Female	0.5804	0.5821	0.0017	(0.5884)
White	0.2939	0.2915	-0.0024	(0.2599)
Asian	0.3144	0.3164	0.002	(0.3374)
Hispanic/Latino	0.2725	0.2734	0.0009	(0.6709)
Black	0.0206	0.0211	0.0005	(0.4180)
EOP Student	0.343	0.3419	-0.0011	(0.6919)
Freshman	0.2453	0.2450	-0.0003	(0.8472)
Sophomore	0.5896	0.5878	-0.0018	(0.3784)
Junior	0.1224	0.1250	0.0026	(0.1070)
Senior	0.0427	0.0419	-0.0008	(0.3474)
Prior Chem 1A Grade	2.8922	2.8911	-0.0011	(0.8041)
Pre-GPA	3.2056	3.2039	-0.0017	(0.4535)

Note: Differences are regression adjusted for lab section fixed effects and classmate composition of specified characteristic. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.2: Regression Coefficients for Main Outcomes

	(1) Numeric score	(2) Grade (4 point scale)	(3) Passed course	(4) Dropped course
Female student with male partner	0.0038	-0.0099	0.0052	-0.0046
	(0.0338)	(0.0154)	(0.0083)	(0.0083)
Male student with female partner	0.0344	0.0021	0.0075	-0.0036
	(0.0520)	(0.0236)	(0.0106)	(0.0101)
Observations	4,968	4,976	5,246	5,246
Mean (Dep. var.)	0.0000	3.8219	0.9476	0.0499
SD (Dep. var.)	1.0000	0.4438	0.2229	0.2178

Note: Standard errors are clustered by lab sections. Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, gender, Educational Opportunity Programs status, year in college, major interest, and declaration of major. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.3: Regression Coefficients for Additional Outcomes

	(1) Takes Organic Chemistry	(2) Declared Chemistry	(3) Declared STEM	(4) Co-current lecture grade
Female student	0.0115	0.0026	-0.0100	-0.0050
with male partner	(0.0165)	(0.0104)	(0.0198)	(0.0319)
Male student	-0.0165	0.0117	-0.0060	0.0360
with female partner	(0.0193)	(0.0146)	(0.0224)	(0.0368)
Observations	5,246	4,878	4,878	4,357
Mean (Dep. var.)	0.6281	0.0976	0.4992	2.9248
SD (Dep. var.)	0.4834	0.2968	0.5001	0.8533

Note: Standard errors are clustered by lab sections. Students that have declared as a STEM major prior to enrolling in the lab are excluded from columns (2) and (3). Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, gender, Educational Opportunity Programs status, year in college, major interest, and declaration of major. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.4: Regression Coefficients for Main Outcomes by Ability of Student

	(1) Numeric score	(2) Grade (4 point scale)	(3) Passed course	(4) Dropped course
<u>Female student</u>				
with low ability partnered to male	0.0568	-0.0039	0.0113	-0.0112
	(0.0550)	(0.0261)	(0.0138)	(0.0139)
with high ability partnerned to male	-0.0434	-0.0232	0.0007	-0.0001
	(0.0370)	(0.0159)	(0.0110)	(0.0109)
<u>Male student</u>				
with low ability partnered to female	0.0136	-0.0084	0.0107	-0.0025
	(0.1111)	(0.0494)	(0.0199)	(0.0187)
with high ability partnerned to female	0.0334	-0.0051	0.0055	-0.0064
	(0.0496)	(0.0215)	(0.0126)	(0.0122)
Observations	4,761	4,769	5,023	5,023
Mean (Dep. var.)	0.0265	3.8335	0.9490	0.0490
SD (Dep. var.)	0.9724	0.4224	0.2199	0.2158

Note: Standard errors are clustered by lab sections. Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, gender, gender by ability, Educational Opportunity Programs status, year in college, major interest, and declaration of major. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5: Regression Coefficients for Main Outcomes by Ability of Partner

	(1) Numeric score	(2) Grade (4 point scale)	(3) Passed course	(4) Dropped course
Female student				
partnered to low ability male	0.0367	-0.0036	-0.0009	0.0031
	(0.0436)	(0.0203)	(0.0112)	(0.0113)
partnered to high ability male	-0.0164	-0.0139	0.0091	-0.0097
	(0.0388)	(0.0175)	(0.0098)	(0.0099)
Male student				
partnered to low ability female	0.0068	-0.0128	0.0040	-0.0005
	(0.0645)	(0.0300)	(0.0124)	(0.0118)
partnered to high ability female	0.0627	0.0174	0.0112	-0.0070
	(0.0563)	(0.0263)	(0.0125)	(0.0121)
Observations	4,963	4,971	5,241	5,241
Mean (Dep. var.)	0.0005	3.8219	0.9475	0.0500
SD (Dep. var.)	0.9998	0.4439	0.2230	0.2179

Note: Standard errors are clustered by lab sections. Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, gender, Educational Opportunity Programs status, year in college, major interest, and declaration of major. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6: Regression Coefficients for Main Outcomes by Ability of Student (By Prior GPA)

	(1) Numeric Score	(2) Grade (4.0 Scale)	(3) Passed Course	(4) Dropped Course
Female Student	0.3658***	0.1538***	0.0184	-0.0085
	(0.0594)	(0.0278)	(0.0127)	(0.0124)
Female High Ability	-0.1452***	-0.0748***	-0.0173	0.0103
	(0.0533)	(0.0254)	(0.0128)	(0.0125)
Female Low Ability X Male Partner	0.0207	-0.0041	-0.0040	0.0043
	(0.0509)	(0.0260)	(0.0133)	(0.0134)
Female High Ability X Male Partner	-0.0188	-0.0137	0.0122	-0.0111
	(0.0367)	(0.0148)	(0.0109)	(0.0109)
Male Low Ability X Female Partner	0.0104	-0.0130	0.0180	-0.0109
	(0.0691)	(0.0335)	(0.0138)	(0.0131)
Male High Ability X Female Partner	0.0553	0.0123	0.0033	-0.0025
	(0.0484)	(0.0213)	(0.0124)	(0.0120)
Observations	4,920	4,928	5,192	5,192
Mean (Dep. Var.)	0.0022	3.8229	0.9482	0.0493
SD (Dep. Var.)	0.9981	0.4426	0.2217	0.2165

Note: Standard errors are clustered by lab sections. Controls include baseline lab section fixed effects, prior GPA, ethnicity, Educational Opportunity Programs status, year in college, major interest, and declaration of major. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.7: Regression Coefficients for Main Outcomes by Ability of Partner (By Prior GPA)

	(1) Numeric Score	(2) Grade (4.0 Scale)	(3) Passed Course	(4) Dropped Course
Female Student	0.2894***	0.1152***	0.0084	-0.0022
	(0.0421)	(0.0195)	(0.0099)	(0.0098)
Female X Low Ability Male Partner	-0.0141	-0.0143	0.0033	-0.0022
	(0.0379)	(0.0176)	(0.0105)	(0.0106)
Female X High Ability Male Partner	0.0241	-0.0009	0.0065	-0.0062
	(0.0400)	(0.0189)	(0.0112)	(0.0114)
Male X Low Ability Female Partner	0.0080	-0.0126	0.0009	0.0022
	(0.0597)	(0.0282)	(0.0127)	(0.0119)
Male X High Ability Female Partner	0.0645	0.0170	0.0166	-0.0120
	(0.0519)	(0.0265)	(0.0121)	(0.0118)
Observations	4,968	4,976	5,246	5,246
Mean (Dep. Var.)	0.0000	3.8219	0.9476	0.0499
SD (Dep. Var.)	1.0000	0.4438	0.2229	0.2178

Note: Standard errors are clustered by lab sections. Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, Educational Opportunity Programs status, year in college, major interest, and declaration of major. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.8: Regression Coefficients for Main Outcomes by Majority Female Lab Sections

	(1) Numeric score	(2) Grade (4 point scale)	(3) Passed course	(4) Dropped course
Female student with male partner				
Majority female lab section	-0.0059	-0.0150	0.0020	-0.0019
	(0.0389)	(0.0185)	(0.0092)	(0.0091)
Not-majority female lab section	0.0132	-0.0020	0.0160	-0.0151
	(0.0681)	(0.0279)	(0.0183)	(0.0183)
Male student with female partner				
Majority female lab section	0.0043	-0.0122	-0.0043	0.0071
	(0.0838)	(0.0360)	(0.0168)	(0.0155)
Not-majority female lab section	0.0502	0.0112	0.0197	-0.0155
	(0.0674)	(0.0317)	(0.0141)	(0.0138)
Observations	4,968	4,976	5,246	5,246
Mean (Dep. var.)	0.0000	3.8219	0.9476	0.0499
SD (Dep. var.)	1.0000	0.4438	0.2229	0.2178

Note: Standard errors are clustered by lab sections. Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, gender, gender by majority gender of lab, Educational Opportunity Programs status, year in college, major interest, and declaration of major. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.9: Regression Coefficients for Main Outcomes by Teaching Assistant Gender

	(1) Numeric score	(2) Grade (4 point scale)	(3) Passed course	(4) Dropped course
Female student with male partner				
Lab section with female TA	-0.0066	-0.0162	0.0012	-0.0010
	(0.0556)	(0.0255)	(0.0117)	(0.0116)
Lab section with male TA	0.0143	-0.0036	0.0081	-0.0074
	(0.0414)	(0.0188)	(0.0119)	(0.0118)
Male student with female partner				
Lab section with female TA	0.0391	0.0066	0.0326**	-0.0284**
	(0.0771)	(0.0341)	(0.0151)	(0.0142)
Lab section with male TA	0.0346	0.0009	-0.0146	0.0182
	(0.0709)	(0.0327)	(0.0146)	(0.0141)
Observations	4,936	4,944	5,212	5,212
Mean (Dep. var.)	-0.0039	3.8211	0.9476	0.0499
SD (Dep. var.)	1.0010	0.4448	0.2228	0.2177

Note: Standard errors are clustered by lab sections. Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, gender, gender by TA gender, Educational Opportunity Programs status, year in college, major interest, and declaration of major. *** p<0.01, ** p<0.05, * p<0.1.

Chapter 3

Race and Science: The Effects of Laboratory TAs on Students

3.1 Introduction

The America COMPETES act and subsequent re-authorization has brought renewed focus to improve national research capabilities by improving the training for future STEM (Science, Technology, Engineering, and Mathematics) workers. To address this goal, the United States has prioritized the development of a well-qualified and increasingly diverse STEM workforce. This initiative attempts to address concerning levels of disparities by race. Under-Represented Minorities (URMs) comprise of 26% of the US residential population over the age of 21, but they only account for 10% of those employed in science and engineering. Consistent with these occupational disparities, URMs only account for 13% of science and engineering degree holders with a bachelors degree or higher (National Science Board, 2015). Under-representation in these fields pose social and economic concerns. Within four years from graduation, STEM bachelors degree holders earn approximately $15,000 more in annual earnings compared to their non-STEM counterparts (Cataldi, Siegel, Shepherd, & Cooney, 2014). Even after adjusting for demographic characteristics and potential labor market outcomes, the gap in wages between majors can be as high as the gap between college degree holders and high school graduates (Altonji, Blom, & Meghir, 2012).

Determining causal factors that affect the post-secondary STEM achievement gap for minority students is particularly challenging. At the post-secondary level, minority students are disproportionately less likely to attend well-resourced institutions (Garcia, 2018). This has adverse consequences. Numerous studies have found the resource level to be important in determining the level of academic success (Bound & Turner, 2007; Bound, Lovenheim, & Turner, 2010; Deming & Walters, 2017). A complementary and alternative explanation for the achievement gap may also be a role model effect (Dee, 2004, 2005; Hoffmann & Oreopoulos, 2009; Fairlie et al., 2014; Lusher et al., 2018; Solanki & Xu, 2018). Role models in classrooms are thought to be important, especially for minority students (Fraga, Meier, & England, 1986; Hess & Leal, 1997). The importance of minority role models may be heighted due to stark under-representation of black and Hispanic faculty in STEM fields (Li & Koedel, 2017).

Previous studies examining the role of minority instructors in post-secondary settings have found positive correlations between minority STEM instructors and student decisions to persist in STEM (Griffith, 2010; Price, 2010). The extent the correlations are an effect is difficult to estimate because the composition of faculty and graduate TAs may be correlated with the quality of an institution. Previous research on University of California system by Arcidiacono, Aucejo, and Hotz (2016) find that the match quality between minority students and campuses is an important determinant of STEM achievement.

This paper adds to previous literature by being the first to quasi-experimentally estimate role model effects with instructor and/or TA race in post-secondary STEM classrooms. Role models that have been examined by race are elementary school teachers (Dee, 2004, 2005), community college instructors (Fairlie et al., 2014), and Economics TAs at a research university (Lusher et al., 2018). Similarly, the role of gender has been examined with university instructors (Bettinger & Long, 2005; Hoffmann & Oreopoulos, 2009), and science professors (Carrell et al., 2010). In the dimension of race, the general findings have been that when students are matched with similar instructors or TAs, students are more likely to persist or perform better.

To explore potential effects stemming from a lack of minority role models in STEM, I examine the extent TA race affects students in introductory chemistry labs at a large and diverse public research university. The analysis uses records from 310 lab sections with 4,690 student-lab level enrollments in introductory Chem Lab courses (Chem 1M and 1N) over four academic years. Each lab section is mandatory and entirely instructed by a graduate student TA. An instructor of record oversees all the TAs and curriculum for the respective course. The data collected for this study involves observations, records from a unified online assignment and grading system, and university administrative records.

Estimates of effects stemming from TA-student interactions are possible due to the timing of TA assignments to lab sections that occurs after student enrollments. Students only learn who their TAs are once they attend their first lab meeting. Unsurprisingly, I find no statistical evidence that students are able to select their lab TA. The empirical strategy which focuses on the interaction of TA race with student race allows for lab-section fixed effects. These fixed effects control for unobservable differences that may arise in each lab including but not limited to TA quality, peer quality, and common shocks. The setting of this study is also ideal due to intensive interactions between TAs and students that are a natural consequence of an enrollment cap of 18 students per lab section.

My estimates show that students are 1.2 percentage points less like to drop a lab course (on a base of 5 percent) when they are assigned a similar race TA. When minority students are assigned minority TAs, I estimate they are 2.3 percentage points less likely to drop a lab course. These estimates have a direct and almost identical effect on their unconditional pass outcomes. Separately, I do not detect any effects on grade performance or effort as measured by the time spent on the online assignment system. I also do not detect effects on passing co-current chemistry lecture classes or future decisions to enroll in organic chemistry, declarations of a major in Chemistry, or a major within STEM.

These estimates are from a sample of students aspiring to major in a diverse set of STEM majors from the biological to physical sciences. The students also come from broad socio-economic backgrounds and are well represented by both genders. Taking the diversity of the student sample into consideration, the results are quite striking. The racial match between students and TAs accounts for over 20 percent of the course drops and potentially more so when comparing minority students to non-minority students. These results suggest that the race of TAs are critical factors in racial achievement gaps.

3.2 Data

3.2.1 Data Sources and Institutional Background

This study utilizes student administrative data, in-person observations, and online gradebooks with detailed assignment records in introductory Chemistry labs from Winter Quarter of 2015 through Spring Quarter of 2018. The Chemistry labs take place at a large, public research university with an approximate undergraduate enrollment of 20,000 students. The students at the university are racially diverse where 31% of students are White, 27% are Asian or Pacific Islander, 25% are Hispanic or Latino(a), and 4% are African-American. 330 Chemistry labs are observed with a capped enrollment of 18 students. Almost all section seats in the registration system are filled prior to the first week of labs. The mean attendance rate on the first lab meeting is 16.8.

The Introduction to Chemistry sequence at the university covers a standard set of topics, similar to other large research universities. The laboratory classes associated with this sequence are also standard. The sequence requires a minimum of pre-calculus before enrolling, but most students have already taken calculus. The sequence involves extensive use of math throughout the coursework. Students generally take Chem 1A, 1B, and 1C in consecutive quarters. The two labs (Chem 1M and 1N) are associated with the second and third quarter courses in the sequence, respectively.

Chemistry labs are taken by students from a wide range of majors across campus. The introductory Chemistry sequence is required for most science majors, and students have large representations from Chemistry, Biology, Bio-Engineering, Neuroscience, Computer Science, Ecology, and Psychology. The laboratory curriculum, grading, physical equipment, and space are standardized across sections. The laboratory equipment and materials are uniformly disbursed from a central laboratories manager. Lab sections are held in eight different laboratory classrooms along one hallway in the Chemistry instruction building. The standardization across lab sections provides an ideal controlled environment to measure social interactions.

Each observation in the dataset corresponds to a student who is enrolled in a Chemistry lab and attends the first section of the quarter. Students are only allowed to enroll in one section per lab (M or N) and are not allowed to switch for the duration of the quarter. To complete the Chemistry lab course, students must attend sections weekly for 8 consecutive weeks. In the case of an excused absence, students may attend a make-up lab. Each lab section is scheduled for 3 hours.

The instruction for each section is solely provided by an assigned graduate TA. This graduate TA is responsible for all the instruction, supervision, and grading of the students enrolled in the lab. One formal instructor of record manages the common curriculum and supervises all the laboratory TAs for each course (Chem M or Chem

N). They formally submit grade records to the institution, but do not participate in laboratory instruction or grading.

An important contribution of this study is the data on student performance from a combined online gradebook and assignment system. In addition to observing the exact numeric grade a student earns from zero to a hundred, I also observe the time students are logged into the online assignment system. All students must be registered and use this system to complete the course. Although it is impossible to observe the effort students expend in a lab, this measurement provides a proxy that systematically approximates student effort without recall or social desirability bias.

The race of students are provided by the university's administrative data system. The race of the TAs are determined by myself. I observe the TA race in person, with pictures on LinkedIn/university websites, and with origin of last names to determine the race of the TAs. I only record their race if all three dimensions corroborate.

3.2.2 Sample Restrictions and Summary Statistics

The focus of this study is to understand how students respond to similar race TAs. A natural limitation is that similarities cannot be identified when students are not classified a race, or are reported as two or more races. This also occurs when TAs have two or more races. In addition, there is a pair of sections co-taught by TAs. The main sample excludes these observations from a full sample of 330 lab sections and 5,536 student observations. The remaining sample consists of 310 lab sections and 4,690 student-lab level observations. Table 3.1 reports these descriptive statistics.

Panel A reports a summary of baseline student characteristics at the student-lab level. The mean Chem 1A grade (where 4.0 is equivalent to an A) is 2.84. This reports the grade students earned in the introductory chemistry course prior to enrolling in the Chem labs. Females account for 58%, Educational Opportunity Programs students account for 36% and over 84% of students are either proposed or declared STEM majors. The racial diversity of the students enrolled in the Chem labs reflect the overall composition of the campus. 2% are African-American or Black, 34% are Asian, 30% are Hispanic or Latina/o, 33% are White, and less than 1% are other minorities (Native-American or Native-Alaskan). A majority of the students are Sophomores (59%) or Freshman (24%), while a minority of students are Juniors (12%) and Seniors (4%).

Panel B reports the gender and racial composition of TAs at the TA-class level. Female TAs account for 45% of the labs instructed. Underrepresented minorities comprise 15% of the instruction where 2% is by African-American or Black and 14% by Hispanic or Latina/o TAs. Asian TAs account for 24% and White TAs account for 61% of the labs instructed.

In Panel C, I document differences in outcomes by race. Asian students are the least likely to drop the lab and have a mean drop rate of 3.8%. African-American or Black students are the second least likely to drop and have a mean drop rate of 4.7%. Hispanic, White, and other minorities have slightly higher drop rates that are approximately 5%. The average grade performance for students across all racial groups are similar and they average 3.8 grade points (4.0 being an equivalent of an A). These match closely with the numeric grades on the online gradebooks. The online assignment system also documents that URMs spend the most time on the assignment system. African-Americans or Blacks spend on average 26.3 hours, Hispanic or Latina/os spend 25.8 hours, other minorities spend 25.2 hours, relative to 24.7 hours by Asians and 23.4 hours by Whites.[1] This panel also reports outcomes that occur outside of lab performance. Asian and White students are most likely to co-currently pass chemistry lecture courses, while African-American or Black, Hispanic or Latina/o, and other minorities are less likely to pass.

The largest differences between races in Panel C appear in student future course enrollments and declaration of majors. Asian, other minorities, and African American or Black students are most likely to enroll in Organic Chemistry while Hispanic or Latina/o and White students are least likely to do so. The declaration of a major in Chemistry shows a slightly different story, where Asian, Hispanic or Latina/o, and White students declare at similar rates, and African-American or Black and other minorities are half as likely to declare as their counterparts. In STEM, White students are the most likely to declare at a rate of 60%. Hispanic or Latina/o follow with 51%, Asian with 47%, African-American or Black with 39% and other minorities at a rate of 33%.

[1] The measure is winsorized at the 10 percent level.

3.3 Empirical Method

3.3.1 The Models

The main model on student-classroom level outcomes is given by

$$y_i = \alpha Similar_i + \beta X_i + \lambda_s + u_i \tag{3.1}$$

where students are indexed by i and laboratory sections by s. The variable $Similar_i$ represents an indicator variable that is equal to one when the student and laboratory TA have a similar race. The variable X_i represents a vector of controls for student characteristics prior to enrolling in section s, and u_i represents the error term. The α parameter measures the relative academic performance when a student is assigned to a similar race TA compared to a dissimilar TA. The focus of similarity between students and TAs allows for section fixed effects as represented by λ_s. This fixed effect implicitly controls for all aspects common and/or unique to lab sections. Importantly, this controls for the assigned TA (e.g., ability, experience, gender, race), lab course (M o N), peers, and all other common shocks associated with the section.

An econometric model focused on minority interactions is given by

$$y_i = \phi MinorityTA \times Minority_i + \theta X_i + \gamma_s + v_i \tag{3.2}$$

where students are still indexed by i and laboratory sections by s. The variable $MinorityTA$ indicates whether the TA is an under-represented minority and $Minority$ indicates whether the student is an under-represented minority. Section fixed effects are represented by γ, and the error term is represented by v. The ϕ parameter is similar to the alpha parameter, but focuses on the extent the relative performance of minority students are affected by being assigned to minority TAs.

3.3.2 Identification

The primary threat to the identification strategy exists if students self-select the race of their lab section TA. In this setting, it is very difficult for students to select their TAs because section enrollments are almost always full with many students already on the waitlists before the prior quarter ends. With a maximum lab section capacity of 18 students, it is very costly to have empty seats in sections. In the instances that sections are over-assigned in the master schedule to the extent seats are left unfilled, the Chemistry department collapses sections to insure they are as close to full capacity before the quarter starts. These course registrations occur well before TAs are assigned to the course they instruct and especially before they are assigned a lab section time and location. The instructors of record also have a long-standing policy of no-section switching once the labs start. Consequently, it is very difficult for students to select the race of their TA.

To test for self-selection, I examine whether observable student characteristics are correlated with TA race and gender conditional on course by term fixed effects. Table 3.2 reports five separate regression tests. The outcome variable for each column is an indicator variable for the TA characteristic. In order of left to right, these characteristics Asian, Hispanic, White, under-represented minority, and Female. The co-varietes of student observable characteristics tested in each of the regressions include, gender, race, prior grade earned in Chem 1A, major, and Educational Opportunity Programs status. Of the 40 coefficients that are tested, only 3 report a p-value of less than 0.1. This empirical test for selection provides confidence that primary regressor of interest is free from selection bias.

3.4 Results

3.4.1 Main Results

The estimates of interactions between students and TAs are presented in Table 3.3 with standard errors clustered by the TA level. Panel A reports estimates by similar race as modeled by equation (3.1) and Panel B reports estimates by minority interactions as modeled by equation (3.2). I examine the sensitivity of estimates by adding additional controls and fixed effects in columns 1 through 5 for the outcome of unconditionally passing a lab course and the outcome of dropping the lab course in columns 6 through 10. The left-most column for each outcome only controls for student and TA race and the course (1M or 1N labs) students are enrolled. The next column replaces a control for the course with course by term fixed effects. The third column also adds an additional set of controls for additional student characteristics that include dummy variables for the full grade distribution in Chem 1A prior to labs, Educational Opportunity Programs status, year in college, major interest, and declaration of major. The fourth column adds fixed effects by each TA. The preferred specification is reported in the final column.

Course by race and TA fixed effects are replaced with lab section fixed effects in this specification. The sensitivity analysis displays that results are robust to the addition of varying controls and fixed effects.

In Panel A, I estimate that students assigned to similar race TAs, are statistically significantly 1.24 percentage points more likely to unconditionally pass a course and 1.21 percentage points less likely to drop a course. Panel B explores the interaction when minority students are assigned a minority TA, and I estimate a slightly larger but statistically insignificant 1.84 percentage point increase in probability of unconditionally passing a course and a statistically significant decrease of 2.33 percentage points in likelihood of dropping a course. The higher precision of estimates in Panel A compared to Panel B are a natural consequence of the higher probability of similar race students being match with a TA, compared to the probability of minority students being matched with a minority TA.

Table 3.4 presents additional course level outcomes as modeled by equation (3.1). Columns 1 and 2 report identical estimates from Table 3.3 and are presented for a reference point. Column 3 reports estimates on grades from TA digital gradebooks normalized to a mean zero with a standard deviation with 1. No statistically significant effects are detected, with a relatively precise 95% confidence interval between -.043 and .069 standard deviations. Column 4 reports estimates on official grades earned. Similarly, this also shows no statistically significant effects. The final column examines the effect on the log of time spent on the online assignment system. This roughly estimates the percentage effect on effort in the lab. This also displays no statistically significant effect, with a 95% confidence interval between -1.7% effect and a 2.1% effect. Students are unlikely to be affected by more than half of an hour relative to a mean rate of 24 hours. Table 3.5 also presents results for the same course level outcomes with the model outlined by equation (3.2). The table displays that the effects are larger when examining the variation of minority TAs matched with minority students.

3.4.2 Co-Current and Subsequent Outcomes

The matching between TAs and students may also have spillover effects on student performance and decisions. Table 3.6 presents these additional outcomes using the main model as outlined by equation (3.1). The first column examines the outcome of passing a co-current Chemistry lecture course. Little or no effect is detected on this outcome. Column two explore the extent which cumulative units earned are affected when students drop a course. Little or no effect is detected in this dimension. The third column examines the effect on cumulative grade point averages (4.0 scale). There is a small and statistically insignificant negative 0.01 estimate on this outcome. The next column examines whether students proceed to enroll in Organic Chemistry. There is statistically insignificant negative 2.3 percentage point effect on this outcome. The fifth column examines whether students ever declare as a Chemistry major and this is a small statistically insignificant estimate. Finally, the last column examines whether students ever declare as a STEM major. Although this estimate is statistically insignificant, the estimated effect is approximately 1.9 percentage points.

3.4.3 Differences Across Sub-samples

Next, I examine for differences across sub-samples by including a triple-interaction on the main specification with an indicator by student characteristic. Table 3.7 reports these estimated effects on course drops with each characteristic interacted separately onto the model column by column. Column 1 presents the main model without a triple interaction for a baseline comparison. The next columns examine differential effects by an indicator for freshman status, earning a below sample median grade in Chem 1A prior to enrolling in the Chem lab, enrolling in a lab section where there is a below median share of similar classmates relative to other lab sections, being a minority, randomly being assigned a similar race Chem lab partner, randomly being assigned a same gender Chem lab, and being Female. I do not detect differential effect by any of the examined characteristic. Most notably, the coefficient representing the reduction in probability of dropping a Chem lab class as a result of being assigned to a similar race TA ranges from a 0.95 to 1.74 percentage points. This suggest that the estimated effects apply broadly across students and are not being driven by sub-samples.

3.4.4 Group by group analysis

In this subsection, I deviate from the main specification to provide insights, group by group. In Table 3.8, I follow the group by group regression specification as reported by Lusher et al. (2018). The table reports coefficients for a single regression interacting the race of TAs with students, while omitting the possible interaction terms when the TA and student race are similar. Each cell in the table represent an interaction by race of TA and student. On both the outcomes of drops and un-conditional passes, that statistically significant coefficients show negative effects when students are unmatched with similar races.

3.5 Conclusion

A critical pathway to science occupations is post-secondary education. A natural concern at these institutions is that minority students may be disadvantaged due to limited opportunities for role models along race in the fields of science. Previous to this study, there has been little or no causal evidence documenting the extent of this disadvantage in STEM courses at a university. I find that race is a significant factor in course persistence behavior. Over 20% of course drops are accounted for by the match of race between students and TAs.

On other measurable outcomes such as grades and time to complete assignments, I do not detect an effect due to student and TA matchings by race. Perhaps this is a natural consequence of a controlled environment where subjective grading is greatly reduced through a uniform and predominantly online graded assignment system managed by scientists. In its entirety, the estimates from this study suggest that the effects stemming from the race of a TA may operate through a behavioral mechanism such as a social cue where students may be assessing risks from previous experiences.

The overall results from this study suggest that an important factor in explaining the minority gap in STEM fields is the race of TAs. With the Black and Hispanic population projected to grow by 64 and 56 percent between 2014 and 2060 relative to an increase of 22 percent by the White population, a lack of minority role models in STEM classrooms is likely to be a factor in perpetuating the current racial gaps in science (Colby & Ortman, 2017).

Table 3.1: Descriptive Statistics

Panel A: Baseline Student Characteristics (Student-Lab Level, n = 4,690)

	Mean	SD
Chem 1A Grade	2.84	1.00
Female	0.58	
Educational Opportunity Programs	0.36	
Proposed/declared STEM	0.84	
Race/ethnicity		
African-American or Black	0.02	
Asian	0.34	
Hispanic or Latina/o	0.30	
White	0.33	
Other Minority	0.00	
Year in college		
Freshman	0.24	
Sophomore	0.59	
Junior	0.13	
Senior	0.04	

Panel B: Lab TA Characteristics (TA-Lab Level, n=310)

	Mean
Female	0.45
Race/ethnicity	
African-American or Black	0.02
Asian	0.24
Hispanic or Latina/o	0.14
White	0.61

Panel C: Student Outcomes (Student-Lab level, n = 4,690)

	African-American or Black		Asian		Hispanic or Latina/o		White		Other Minority	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Dropped	0.05		0.04		0.05		0.06		0.06	
Passed (Un-Conditional)	0.95		0.96		0.94		0.94		0.94	
Numeric Grade (100)	92.49	4.27	93.78	5.13	92.20	5.68	92.86	5.60	92.92	4.29
Letter Grade (4.0)	3.82	0.35	3.88	0.36	3.77	0.50	3.81	0.47	3.81	0.36
Hours On Web Assignments	26.32	8.73	24.73	7.75	25.77	7.84	23.38	7.35	25.21	7.04
Units Earned (During Quarter)	16.12	3.90	17.12	3.86	16.30	4.24	16.46	3.81	16.17	2.46
Cumulative GPA (At End of Quarter)	3.11	0.45	3.23	0.44	3.03	0.44	3.25	0.45	3.16	0.37
Passed Co-Current Lecture Course	0.79		0.84		0.79		0.82		0.78	
Enrolls in Organic Chemistry	0.66		0.72		0.62		0.54		0.67	
Declares a Major in Chemistry	0.05		0.10		0.10		0.11		0.06	
Declares a major in STEM	0.39		0.47		0.51		0.60		0.33	
n	107		1601		1420		1544		18	

Notes: Other minorities include Pacific Islanders and Native Americans.

Table 3.2: Tests For Sorting

	(1) Asian TA	(2) Hispanic TA	(3) White TA	(4) URM TA	(5) Female TA
Female	-0.0128	0.0135	-0.0012	0.0140	-0.0178
	(0.0120)	(0.0182)	(0.0175)	(0.0180)	(0.0157)
Asian	-0.0370**	0.0222	0.0166	0.0204	-0.0234
	(0.0150)	(0.0150)	(0.0179)	(0.0150)	(0.0204)
Hispanic or Latina/o	0.0168	-0.0051	-0.0146	-0.0022	-0.0010
	(0.0175)	(0.0162)	(0.0208)	(0.0164)	(0.0189)
African-American or Black	0.0261	0.0112	-0.0353	0.0092	-0.0284
	(0.0378)	(0.0355)	(0.0412)	(0.0357)	(0.0465)
Other Minority	-0.0186	-0.0299	0.0476	-0.0290	-0.0239
	(0.0924)	(0.0665)	(0.1020)	(0.0666)	(0.0920)
Chem 1 Grade (Prior to Lab)	0.0064	-0.0004	-0.0095	0.0031	-0.0012
	(0.0061)	(0.0046)	(0.0077)	(0.0053)	(0.0076)
Proposed/Declared STEM (Prior to Lab)	0.0158	0.0232	-0.0421**	0.0263*	-0.0199
	(0.0172)	(0.0154)	(0.0185)	(0.0155)	(0.0185)
Educational Opportunity Programs	-0.0141	0.0008	0.0102	0.0040	-0.0219
	(0.0125)	(0.0068)	(0.0132)	(0.0071)	(0.0154)
Observations	4,690	4,690	4,690	4,690	4,690
R-squared	0.1694	0.0987	0.1474	0.1109	0.1533
Dep Var Mean	0.2945	0.1525	0.5461	0.1595	0.4367

Notes: Each column presents results for a regression where the dependant variable is the TA characterstic. Additonal controls include baseline lab section fixed effects. Standard errors are clustered by teaching assistant. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.3: Main Results

	Unconditonally Passed Course					Dropped Course				
Panel A:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Similar Race	0.0097*	0.0109**	0.0097*	0.0114**	0.0124**	-0.0096*	-0.0106**	-0.0095*	-0.0112**	-0.0121**
	(0.0051)	(0.0050)	(0.0050)	(0.0052)	(0.0058)	(0.0051)	(0.0049)	(0.0050)	(0.0052)	(0.0059)
Observations	4,690	4,690	4,690	4,690	4,690	4,690	4,690	4,690	4,690	4,690
R-squared	0.0166	0.0277	0.0381	0.0553	0.1055	0.0154	0.0259	0.0356	0.0524	0.1044
Dep Var Mean	0.9475	0.9475	0.9475	0.9475	0.9475	0.0499	0.0499	0.0499	0.0499	0.0499
Panel B:										
URM TA X URM	0.0128	0.0149	0.0125	0.0169	0.0184	-0.0164	-0.0188*	-0.0164	-0.0220*	-0.0233*
	(0.0098)	(0.0103)	(0.0108)	(0.0111)	(0.0127)	(0.0103)	(0.0098)	(0.0109)	(0.0112)	(0.0131)
Observations	4,690	4,690	4,690	4,690	4,690	4,690	4,690	4,690	4,690	4,690
R-squared	0.0164	0.0274	0.0378	0.0550	0.1051	0.0152	0.0257	0.0354	0.0522	0.1042
FE										
Course (M or N)	X					X				
Course X Term		X	X	X			X	X	X	
TA				X					X	
Lab Section					X					X
Additional Controls			X	X	X			X	X	X
Dep Var Mean	0.9475	0.9475	0.9475	0.9475	0.9475	0.0499	0.0499	0.0499	0.0499	0.0499

Notes: All regressions control for student and TA race. Additional controls include dummy variables for the full grade distribution in Chem 1A prior to labs, Educational Opportunity Programs status, year in college, major interest, and declaration of major. Standard errors are clustered by teaching assistant. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4: Results for Course Outcomes

	(1) Passed	(2) Dropped	(3) Grade - Standardized	(4) Letter Grade	(5) Log of Time Online
Similar Race	0.0124**	-0.0121**	0.0131	-0.0011	0.0020
	(0.0058)	(0.0059)	(0.0287)	(0.0141)	(0.0097)
Observations	4,690	4,690	4,444	4,451	4,437
R-squared	0.1055	0.1044	0.2808	0.1726	0.1873
Dep Var Mean	0.9475	0.0499	0.0000	3.8211	3.1541
Dep Var SD	0.2230	0.2177	1.0000	0.4434	0.3198

Notes: Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, Educational Opportunity Programs status, year in college, major interest, and declaration of major. Standard errors are clustered by teaching assistant. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5: Results for Course Outcomes Usings Minority Interactions

	(1) Dropped	(2) Passed	(3) Grade - Standardized	(4) Letter Grade	(5) Log of Time Online
Minority TA X Minority	-0.0235*	0.0187	-0.0219	-0.0072	0.0137
	(0.0130)	(0.0127)	(0.0754)	(0.0364)	(0.0200)
Observations	4,690	4,690	4,444	4,451	4,437
R-squared	0.1042	0.1050	0.2807	0.1726	0.1860
Dep Var Mean	0.0499	0.9475	0.0000	3.8211	3.1541
Dep Var SD	0.2177	0.2230	1.0000	0.4434	0.3198

Notes: Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, Educational Opportunity Programs status, year in college, major interest, and declaration of major. Standard errors are clustered by teaching assistant. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.6: Results for Additional Outcomes

	(1) Passed Co-Current Lecture Course	(2) Units Earned During Quarter	(3) Cumulative GPA	(4) Takes Organic Chemistry	(5) Declared Chemistry	(6) Declared STEM
Similar Race	0.0093	-0.0243	-0.0122	-0.0227	-0.0072	-0.0188
	(0.0129)	(0.1790)	(0.0109)	(0.0147)	(0.0101)	(0.0161)
Observations	4,690	4,690	4,690	4,690	4,690	4,690
R-squared	0.2429	0.2716	0.4889	0.1862	0.1391	0.1660
Dep Var Mean	0.8177	16.4897	3.1725	0.6305	0.0987	0.5239
Dep Var SD	0.3861	4.2440	0.4543	0.4827	0.2983	0.4995

Notes: Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, Educational Opportunity Programs status, year in college, major interest, and declaration of major. Standard errors are clustered by teaching assistant. *** p¡0.01, ** p¡0.05, * p¡0.1.

Table 3.7: Results for Additional Outcomes

	(1) Base	(2) Freshman	(3) Below Median Chem 1A Grade	(4) Below Median Share Similar Race Labmates	(5) URM	(6) Same Race PT	(7) Same Gender PT	(8) Female
Similar Race	-0.0121**	-0.0112*	-0.0095	-0.0174*	-0.0113	-0.0126*	-0.0166*	-0.0133
	(0.0059)	(0.0064)	(0.0074)	(0.0100)	(0.0083)	(0.0066)	(0.0092)	(0.0108)
Similar Race X 1(Characteristic)		-0.0040	-0.0061	0.0095	-0.0039	0.0021	0.0086	0.0021
		(0.0132)	(0.0152)	(0.0135)	(0.0192)	(0.0172)	(0.0117)	(0.0138)
Observations	4,690	4,690	4,690	4,690	4,690	4,690	4,690	4,690
R-squared	0.1044	0.1044	0.1045	0.1045	0.1044	0.1044	0.1045	0.1044
Dep Var Mean	0.0499	0.0499	0.0499	0.0499	0.0499	0.0499	0.0499	0.0499
Dep Var SD	0.2177	0.2177	0.2177	0.2177	0.2177	0.2177	0.2177	0.2177

Notes: Each column reports a regression with an additional interaction. Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, Educational Opportunity Programs status, year in college, major interest, and declaration of major. Standard errors are clustered by teaching assistant. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.8: Results With Interaction By Race

	Unconditonally Passed Course			Dropped Course		
	Asian TA	Hisp TA	White TA	Asian TA	Hisp TA	White TA
Asian	x	-0.0501*	0.0012	x	0.0478*	-0.0072
	x	(0.0280)	(0.0383)	x	(0.0282)	(0.0383)
Hispanic	-0.0781***	x	-0.0583***	0.0774**	x	0.0559***
	(0.0293)	x	(0.0170)	(0.0292)	x	(0.0172)
White	-0.0273	-0.0111	x	0.0290	0.0175	x
	(0.0361)	(0.0438)	x	(0.0356)	(0.0440)	x

Notes: Each outcome is a single regression. The ommitted categories are the similar race interactions (represented by the diagonal). Controls include baseline lab section fixed effects, dummy variables for the full grade distribution in Chem 1A prior to labs, ethnicity, Educational Opportunity Programs status, year in college, major interest, and declaration of major. Standard errors are clustered by teaching assistant. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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