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TAs like me: Racial interactions between graduate teaching assistants and undergraduates[☆]

Lester Lusher[a], Doug Campbell[b], Scott Carrell[c,d,*]

[a] University of Hawaii at Manoa, United States
[b] New Economic School, Russia
[c] University of California, Davis, United States
[d] National Bureau of Economic Research, United States

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ABSTRACT

Using administrative data from a large, diverse university in California, we identify the extent to which the academic outcomes of undergraduates are affected by the race/ethnicity of their graduate student teaching assistants (TAs) in economics courses. To overcome selection in course taking, we exploit the timing of TA assignments, which occur after students enroll in a course, and use within class and within student variation in TA-student race composition. Focusing on an Asian vs. non-Asian split, results show a positive and significant increase in course grades when students are assigned TAs of a similar race/ethnicity. These effects are largest in classes where TAs were given advanced copies of exams and when exams were not multiple choice. We find positive racial correlations between students and TAs at office hours and discussion sections, suggesting student attendance responds to TA race. We also find some evidence of persistent effects: Racial match improves subsequent student performance in sequenced courses, and positively influences decisions on majoring and future course enrollment for Freshmen and Sophomores. Overall, our evidence is consistent with TA-student match quality gains and role model effects.

1. Introduction

For the past twenty years, the United States has steadily fallen relative to other developed countries in college completion rates. From 1995 to 2012, the US went from having the highest young-adult college completion rate among OECD countries to nineteenth. [1] Especially alarming is the fact that US college completion rates have stagnated *despite* increases in overall college attendance (Turner, 2004; NCES, 2017) and large increases in the returns to a college education in the US (Oreopoulos and Petronijevic, 2013). Underlining these college completion rates are prominent racial gaps. In 2015, over 50% of Asian adults aged 25 and older held a bachelor's degree or higher, compared to roughly a third of non-Hispanic Whites and less than 20% of all other races (Ryan and Bauman, 2016). Such differences in postsecondary educational attainment could lead to persistent income inequality across racial groups (Altonji and Blank, 1999; Card, 1999; Jencks and Phillips, 1998).

A natural question to ask is, once students enter college, what factors determine the likelihood they succeed and graduate? Several prior studies have presented causal evidence on various university inputs that influence undergraduate success, including capacity constraints and resources (Bound et al., 2010, 2012), professor quality, gender, and race (Hoffmann and Oreopoulos, 2009b; Carrell and West, 2010; Hoffmann and Oreopoulos, 2009a; Carrell et al., 2010; Fairlie et al., 2014), coaching and advising (Bettinger and Baker, 2014; Angrist et al., 2009), and academic probation (Lindo et al., 2010).

One glaring omission from this literature centers on teaching assistants (TAs), who account for nearly 15% of the total employment of postsecondary teachers in the US annually (Bureau of Labor Statistics, Occupational EmploymentStatistics, 2016). TAs are graduate students employed by a university who perform various duties in the course while under the supervision of a professor or lecturer. Many of these

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* Corresponding author at: Department of Economics, University of California, Davis, One Sheilds Ave., Davis, CA 95616, United States.
E-mail address: secarrell@ucdavis.edu (S. Carrell).
[1] Twenty-eight member countries in 2012 were considered for the study.

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duties impact student success in the course, including 1) hosting small weekly discussion sections, 2) holding office hours, 3) tutoring, 4) proctoring exams, 5) grading assignments and exams, and 6) arranging meetings with students. TA-student relationships are unique in that they are more likely to be a peer-based interaction, since the typical age gap between undergraduates and TAs is relatively small.[2] Additionally, with class sizes and student-professor ratios increasing in the US (Cuseo, 2007; Kokkelenberg et al., 2008; Schanzenbach, 2014), TAs are likely to play an increasingly important role in the US postsecondary education system.

In this paper, we begin to shed light on the importance of TAs in the education production function. To do so, we focus on the role of TA race. Understanding how TA race influences student outcomes is particularly important given recent trends in the US. For the past 40 years, undergraduate and graduate programs have been experiencing a dramatic shift in student racial composition. In 1976, 82% of students enrolled in undergraduate programs in the US were White, compared to only 57% in 2013. A similar pattern can be observed in post-baccalaureate programs, where over the same time period, the fraction of Asian students has more than tripled.[3] Much of the recent shift in racial composition in the US can be attributed to large influxes in international students, particularly from Asian countries. The total number of international students nearly doubled from 1990 to 2012, far outpacing the growth of domestic students; moreover, not only do the majority of these students come from Asian countries, but the fraction of international students hailing from Asia has also risen, from under 56% in 2001 to over 68% in 2015 (Shih, 2017; IIE, 2002; IIE, 2016).[4]

Why might students be influenced by TA race? Role model effects are often mentioned as an important determinant affecting educational outcomes. Another factor might include racial differences in the students' academic expectations. Research from psychology and sociology suggests that equally skilled students of different races may perform differently due to the students' self-belief about their ability to succeed, and these gaps may be muted (or exacerbated) by the TA's race (Spencer et al., 1999). Another channel is a match quality effect, where TAs of different races may have, on average, particular teaching styles or capabilities which are better suited to students of similar race.[5] Finally, TAs may exhibit bias, consciously or unconsciously, with respect to how they treat students of a similar race.

Numerous studies have investigated the importance of student-teacher interactions at the postsecondary level, with a majority focusing on the role of professor gender. Early studies found mixed results, though these studies likely suffer from potential selection biases (e.g., Rothstein, 1994; Canes and Rosen, 1995; Neumark and Gardecki, 1998). More recent studies, which have exploited within class and within student variation to overcome selection issues, have found positive same-gender effects on course grades, choice of major, course credits, and course dropping (Bettinger and Long, 2005; Hoffmann and Oreopoulos, 2009a,b). Likewise, using random assignment to courses, Carrell et al. (2010) find that professor gender has a significant impact on female students' performance in STEM courses. Finally, most closely related to our study, Fairlie et al. (2014) focus on student-professor race interactions at a community college and find that race plays a large role in student outcomes.[6]

In this study, we investigate the importance of TA race. Our primary analyses utilize over 60,000 student-class observations across an eight year period (2003–2011) from a public university in California, coupled with TA assignment data from the university's Department of Economics. The institution we study is large and racially-diverse. In 2014, of the over 34,000 students enrolled, 39% were Asian or Pacific Islander, 19% were Hispanic, and 29% were White. Our data also include a survey that was offered to all professors who taught an economics class during the period of our study, which asked about exam structure (multiple choice vs. essay) and whether exams were shared with TAs prior to the exam date. Lastly, our data include an audit study conducted in 2015 which recorded student attendance during optional TA discussion sections and office hours.

We consider several empirical strategies to identify the causal effects of TA-student racial interactions and to overcome concerns of potential selection bias. Our primary analyses focus on models with class fixed effects, where we estimate differences in outcome variables between students across different races when assigned to the same TAs within the same class.[7] Since the explanatory variable varies both within class, across students, and within student, across classes, the data also allow us to control for sorting that occurs across classes by simultaneously including student fixed effects with class fixed effects. Furthermore, we find no evidence of endogenous sorting into classes by student race when predicting the race of the class' TAs with a full set of controls, including professor race and gender, student gender, high school GPA, age, class standing, and major. The lack of evidence of endogenous sorting is unsurprising for several reasons. First, the primary course registration period for undergraduates occurs before TA assignments are generated by the department. Secondly, once generated, the department only privately reveals the TA assignments to the corresponding professors and TAs.[8]

Our results show that students perform better in classes taken with TAs who are of a similar race. Using Asian vs. non-Asian groupings, we predict a 7.7% of a standard deviation increase in course grade for students who are assigned to TAs of similar race, relative to being assigned to TAs of dissimilar race. This result is robust across various specifications, racial categorizations, and subsamples; as a falsification test, we also find that course grades are uninfluenced by the racial composition of a student's TAs in future courses. We also find some suggestive evidence of longer-run effects. Performance in the second course of a two-course sequence is significantly improved when the student was racially matched to TAs in the first course. Moreover, racial matching appears to influence student subsequent enrollment decisions, where Freshmen and Sophomores are more likely to major in economics and enroll in another economics class after taking a class with similarly-raced TAs.

Lastly, we examine the audit study and professor survey to further investigate the mechanisms potentially driving the results. From the

[2] Several studies have focused on the potential benefits of peer-based mentoring and tutoring. For example, Castleman and Page (2015) find that near-aged peer mentors in college who sent text messages during the summer to college-intending high school graduates substantially increased subsequent college enrollment.

[3] U.S. Department of Education, National Center for Education Statistics, Higher Education General Information Survey (HEGIS), "Fall Enrollment in Colleges and Universities" surveys, 1976 and 1980; Integrated Postsecondary Education Data System (IPEDS), "Fall Enrollment Survey" (IPEDS-EF:90); and IPEDS Spring 2001 through Spring 2014, Enrollment component.

[4] See Shih (2017) for an investigation on the impacts of the recent growth in international students on domestic students' outcomes.

[5] This channel includes language matching where all else equal, a student learns more if particular material can be taught in the student's native language, and students who share the same race as their TAs are more likely to share the same native language.

[6] A handful of other studies have looked at graduate students overall as educators (e.g., Borjas, 2000; Fleisher et al., 2002; Bettinger and Long, 2004; Marvasti, 2007). Of these, Borjas (2000) and Marvasti (2007) focus on the role of nationality, using identical data sets. The authors examined student grades in response to foreign-born TAs across three introductory economics courses with an undisclosed number of teaching assistants. They find that students with international TAs received lower (self-reported) grades, and these results were particularly strong for native students.

[7] We define class as a combination of a course (e.g., Introductory Microeconomics), term (e.g., Fall 2010), and lecture (e.g., "Lecture A", which meets MWF from 10:00to 10:50 am with Professor Lush). For popular courses, several lectures may be offered within the same term such that each lecture constitutes a different class. TAs are never assigned to more than one class within a term.

[8] In other words, TAs and professors themselves do not know which classes TAs are assigned to by the time most undergraduates enroll. While undergraduates still have the ability to register for courses after the end of the primary registration period, the majority of classes fill up by the time this period is over, leaving little capacity for students to be selective with their courses.

audit study, results show that students are more likely to attend their TAs' optional discussion sections and office hours when the TA is of a similar race, providing direct evidence of students responding to similarly-raced TAs. We also see that racial interaction effects are especially prominent in classes where TAs had been given copies of the exams prior to the exam dates. We interpret this result as evidence of "teaching to the exam", where TAs, perhaps unconsciously, divulge information that is pertinent to the exams. Students who attend the TAs' discussion sections and office hours are the beneficiaries of teaching to the exam, and attending students tend to be of similar race as the TAs.[9]

Racial interaction effects are also strongest in classes which had no multiple choice questions on the exams. This result could stem from several possible explanations. First, critical thinking is typically a key component to success on essay-based questions, and critical thinking skills may be fostered in settings where students discuss and ask questions about the course material, such as in TA discussion sections and office hours. Another explanation suggests that TAs are responding to students of similar race when grading.[10] Classes with no multiple choice exams are classes where TAs exercise subjective judgment when grading, and students of specific races may be more likely to answer non-multiple choice questions in a manner in which TAs of a similar race favor.[11]

The remainder of this paper proceeds as follows. Section 2 introduces the data. Section 3 discusses our identification strategies and econometric specifications. Section 4 presents our results. Section 5 discusses the potential underlying mechanisms of our results and policy implications, and Section 6 concludes.

2. Data

2.1. Data sources and institutional background

Our paper centers on detailed student administrative data from a large, public university in California with a highly diversified student community. In 2014, over 34,000 students enrolled at the university, where 39% of the enrolled students were Asian or Pacific Islander, 19% were Hispanic, and 29% were White. U.S. News & World Report (2015) classifies the university admissions as "most selective" and ranks the university as one of the best public university in the United States. Our primary analyses link the student administrative data to graduate teaching assistant (TA) assignment data from the university's Economics Department. The B.A. in economics is the second largest major at the university, accounting for over 6% of degrees conferred annually. These data cover the academic school years from 2003 to 2011 for the three primary quarters of enrollment: Fall, Winter, and Spring.[12]

Each observation in our primary data set pertains to a student who enrolls in an economics class. We define a class as a combination of a course (e.g., ECN100), a term (e.g., Fall 2010), and a "lecture" (e.g., "Lecture A", which meets MWF from 10:00 to 10:50 am with Professor Lush). Every term, the department offers a series of courses. These course-terms typically constitute a single "class" which has a single syllabus, professor, and up to three TAs. For very popular courses, sometimes the department will offer multiple "lectures" within a single term; though they share the same course-term, these lectures are very different classes, as they each contain their own syllabus, meeting times, exams, TA(s), and (almost always) professor.[13] We have a series of student-level characteristics, including term admitted, admission basis (freshman vs. transfer), gender, race, nationality, parental education, and high school GPA. Student-by-term level variables include academic standing (Freshman/Sophomore/Junior/Senior), major(s) when they registered for the course, and age. Finally, class-level controls include professor gender and race.

We match each student-by-class observation to TAs assigned to the class. Since a single class may contain up to three TAs, we do not necessarily analyze one-to-one matches between a student and a TA. In economics courses, a student is technically assigned to a single TA, but often has the liberty to choose any of the TAs in their class to attend discussion sections, visit office hours, etc. Furthermore, TAs within a class jointly share numerous responsibilities, including assisting with lectures and grading assignments and exams. Consequently, as described in further detail in Section 3, we link the race of a student enrolled in a class to the racial composition of the TAs assigned to the class.

Lastly, our paper utilizes two supplemental sets of data. First, in the Fall of 2014, a survey was offered to all professors who taught a class during our 2003 to 2011 time frame. For each class a professor taught, the survey recorded 1) whether the professor shared a copy of the class' exams with the TAs prior to the exam date and 2) the structure of the exams (multiple choice vs. short/long answer).[14] Approximately 58% of our total student-by-class observations are covered by professor survey responses. Secondly, in the Spring 2015 quarter, an audit study was conducted where student attendance by gender and broad racial categories at TA discussion sections and office hours was recorded by an undergraduate research assistant who audited the class. TA discussion sections and office hours are hosted weekly throughout the quarter, and attendance in this setting is optional for enrolled students. Auditors visited the TA discussion sections during the third and fourth weeks of the term and the office hours during the fifth and sixth weeks. The audit study covers 124 discussion sections and 102 office hours.

2.2. Summary statistics

The main outcome variable of interest is the grade each student received in each class, conditional on staying enrolled. Following the classical American letter grading system, at the end of the term, each professor assigns a letter grade (with +/− modifiers) to each student in his/her classes based on the student's performance on class assignments and exams. Each letter grade then gets translated by the university into a numerical grade point average (GPA) value (e.g., $A = \frac{12}{3} = 4.0$, $A - = \frac{11}{3} \approx 3.7$, $F = 0$). For each class, professors are asked to attain an average GPA around 2.7, though professors are given discretion to deviate from this average. For our primary analyses, we standardize each student-by-class grade to a mean of zero and a standard deviation of one by class, and call this variable "Standardized grade". Another outcome of interest is "Passed class", which is an indicator that switches on if the student received a C $-$ ($\frac{5}{3}$ in GPA units) or

[9] Given we also find improvements in subsequent course performance in two-course sequences, it could be that sharing the exam improves the teaching efficacy of the TAs such that the knowledge gained by students in the first course carries over into the second course.

[10] Other studies have found gender biases in teacher grading at the secondary school level (Lavy and Sand, 2015).

[11] Discussed in further detail later in this paper, even if grading biases were a significant channel driving the racial matching effects, studies suggest that such "grade inflation" could still lead to substantial positive human capital gains (Dee et al., 2016; Diamond and Persson, 2016). We do not believe this to be the primary channel in our setting, however, since the gains we observe in subsequent performance are restricted to two-course sequences, where knowledge spillovers are especially pertinent.

[12] Hence, we do not focus on any special quarters, such as summer sessions.

[13] For instance, Principles Microeconomics for the Fall 2011 term could have had two different "classes", where the first class was taught by Professor Xavier with TAs Scott, Logan, and Jean, while the second class was taught by Professor Oak with TAs Ashe and Brock. To make a distinction between these two course-terms, we say that they have different "lectures". These two classes each have different professors, TAs, meeting times, exams, etc. Of the 614 classes in our sample, only 16 (eight pairs) share the same course-term-instructor; these 16 classes still have their own meeting times, exams, and TAs. Our results remain relatively unchanged when we omit these 16 classes (Appendix Table A.16).

[14] Valid responses to the question of sharing exams with the TAs included "Yes", "No", "Sometimes", and "I don't remember". When using this question for analyses, we only focus on the sample of responses that were either "Yes" or "No".

Table 1
Descriptive statistics.

	Mean	(SD)	Observations
Panel A. Sample characteristics, student level			19,522
High school Grade Point Average (GPA)	3.641	(0.360)	
Male	0.528		
Admitted as transfer	0.201		
International student	0.039		
First generation college student	0.388		
Race/ethnicity:			
–African-American	0.021		
–Chinese	0.276		
–Filipino	0.035		
–Japanese	0.018		
–Korean	0.043		
–Latino	0.098		
–Vietnamese	0.068		
–White	0.332		
Panel B. Sample characteristics, TA level			255
International student	0.531		
Male	0.678		
Race/ethnicity:			
–Chinese	0.254		
–Japanese	0.012		
–Korean	0.133		
–Latino	0.071		
–White	0.420		
–Other Asian	0.043		
–Other non-Asian	0.067		
Panel C. Sample characteristics, class level			614
Number of students registered	117.417	(83.147)	
Professor White	0.713		
Professor Asian	0.138		
Professor Hispanic	0.044		
Panel D. Sample characteristics, student-class level			60,642
Age	20.790	(2.089)	
# of Units up to class	75.487	(53.496)	
Economics major	0.471		
Double major	0.085		
Panel D. Student outcomes, student-class level	White	Asian	Other/Minority
Numeric course grade (range: 0 to 4)	2.552	2.756	2.348
Observations: 57,718	(1.015)	(0.988)	(1.074)
Dropped class	0.010	0.010	0.019
Observations: 60,642			
Passed class	0.840	0.877	0.780
Observations: 59,121			
Enroll in an Economics class in future term	0.643	0.605	0.608
Observations: 60,642			

Notes: Panel A corresponds to student-level, Panel B to TA level, Panel C to class level, and Panel D to student-class level descriptive statistics. The student outcome variable "Numeric course grade" corresponds to the standard numerical American grading system with +/− modifiers (e.g., $A = \frac{12}{3} = 4.0$, $A- = \frac{11}{3} \approx 3.7$, $F = 0$).

higher, or a "Pass" in the class.[15] Later analysis also considers ordered logit and ordered probit specifications using the raw letter grades as outcomes.

Table 1 presents summary statistics for our main sample of interest. We have 60,642 student-by-class observations, 19,522 students, 614 classes, and 255 teaching assistants. From Panel A, over 50% of students were male, and nearly 4% of students are identified as international, while the average high school (weighted) GPA for students was 3.64. Panel C reveals that on average, over 117 students enrolled in each class, over 70% of professors were White, and nearly 14% of professors were Asian. Consistent with the notion that classes are difficult to get into, Panel D shows that under 2% of students drop the class once they successfully enroll. "Numeric course grade" in Panel D corresponds to the numerical grade the student received in the class, which ranges between 0 (for F) and 4 (for A). White students received an average class grade of 2.55, while Asian students received an average grade of 2.76. The standard deviation of GPA is around one grade point unit, so the distance between two letter grades (e.g., C vs. B) is roughly one standard deviation. Over 80% of students passed their classes. From Panel A, we find that almost half of the students were Asian, while nearly a third were White. These percentages are similar for the TAs in our sample (Panel B), where roughly 44% of TAs were Asian and 42% were White.[16,17]

3. Econometric specifications

Our primary analysis estimates specification Eq. (1) below, where we racially categorize our students and TAs as either being Asian or non-Asian. We focus on an Asian vs. non-Asian split for two primary reasons. First, statistical power is likely the strongest for such a split since nearly half of the students and TAs in our sample are Asian (Table 1). Secondly, focusing on an Asian split is perhaps the most natural divide to consider, given the recent large shifts in the Asian composition of undergraduate and graduate programs:[18]

$$y_{ikt} = \psi(Asian_i{*}AsianTA_{ikt}) + \beta X_{it} + \lambda_{kt} + \alpha_{kA} + \delta_{tA} + u_{ikt} \quad (1)$$

where y_{ikt} is an outcome for student i taking course k in school term t, $Asian_i$ is an indicator variable for whether student i is Asian, $AsianTA_{ikt}$ is the fraction of student i's TAs for class kt that were Asian, X_{it} is a vector of student-by-term controls, and λ_{kt}, α_{kA}, and δ_{tA} are class, course-by-race, and term-by-race fixed effects, respectively. Since the number of TAs assigned to a class ranges from one to three, $AsianTA_{ikt}$ carries a value of either 0, $\frac{1}{3}$, $\frac{1}{2}$, $\frac{2}{3}$, or 1.

The core of our identification strategy centers on class fixed effects λ_{kt}, which control for unobserved factors that vary at the class level and affect student performance. Note that class fixed effects also control for professor fixed effects since each class is taught by exactly one professor. These, in turn, control for the possibility that students of a particular race take classes with professors who are systematically

[15] At some point toward the beginning of the term, students can opt to receive a grade of either "Pass" (P) or "No Pass" (NP) on their transcript for their class, even though the class is otherwise graded using the standard letter grading system. At the end of each term, professors submit the letter grades received by each student in the class to the registrar's office, and for students who switched into P/NP grading, the registrar converts all grades above and including C− to P, while grades below C− get converted to a NP. For this subset of students, we can only observe their final P or NP grade, and not the letter grade they received prior to the conversion.

[16] A student/TA/professor is classified as of Asian race if their primary race is recorded as Chinese, Japanese, Korean, Filipino, South-East Asian, Vietnamese, Thai, or "Other Asian". TA race was collected by utilizing a combination the TAs' names, information on the TAs' personal websites (e.g., pictures, CVs), and intermediaries' personal knowledge of the TAs.

[17] Given these summary statistics, we can also turn to the Integrated Postsecondary Education Data System (IPEDS) to consider how generalizable our findings may be to other universities. The fraction of White students in our sample compares similarly to that of all other California universities, where 27.1% and 36.9% of undergraduate and graduate students were White, respectively. On the other hand, our sample has a smaller share of minorities and a larger share of Asian students, as roughly 22% of California undergraduates were Asian and 50% were from a minority background. For other observable characteristics, undergraduates in our sample appear similar to the average undergraduate attending a US research university. IPEDS uses the basic Carnegie Classification of Institutions of Higher Education (2010) to determine the list of research universities. For instance, the 25th (75th) percentile SAT Math score for undergraduates at research universities was 558 (667), compared to 560 (680) for our sample. Our sample contains 47% female students, compared to 51% of undergraduates at research universities. Approximately 5% of students from research universities come from a foreign country, and the age profile of undergraduates also looks broadly similar.

[18] Analyses saved for the Appendix consider a White vs. non-White split, as well as finer racial categories. Results remain fairly robust to various racial categorizations.

different from other professors. Class fixed effects also avoid the need to rely on settings with standardized grading or testing procedures across classes since students within a class are completing the exact same assignments and tests. Thus, we are solely comparing the academic performances of Asian and non-Asian students within the same class and subjecting the students to the same class-level shocks, such as the professor's and TAs' characteristics (e.g., ability/experience) or the time/size of the class. Course-by-race fixed effects allow for racial differences in the outcome variable to vary across courses. These are necessary to account for the possibility that the courses in which non-Asians and Asians tend to perform differently are also the courses in which TAs tend to be non-Asian or Asian, respectively.[19] Term-by-race fixed effects account for the possibility that the academic capabilities of Asian or non-Asian students are changing over time. The coefficient ψ measures the average outcome gain for Asian students, relative to non-Asian students, from assignment to Asian TAs. Conversely, ψ measures the average outcome loss for non-Asian students, relative to Asian students, from assignment to Asian TAs versus non-Asian TAs.

To measure student attendance-by-race to TA discussion sections and office hours from the audit study, we consider the following specification:

$$fracStudentAsian_s = \rho AsianTA_s + \beta X_s + u_s \qquad (2)$$

where each observation corresponds to TAs' discussion sections or office hours. X_s comprises of indicators for the weekday, the time, and the individual auditor for the discussion section or office hour.[20] Observations are weighted by total attendance of students to the discussion section or office hour. The coefficient ρ is the expected increase in the fraction of attendees who are Asian in response to the discussion section or office hour being hosted by an Asian TA.

3.1. Identification

The primary threat to our identification strategy is self-selection into courses by TA race, which could result in a correlation between unobserved variables in the error term u_{ikt} and the interaction term $Asian_i * AsianTA_{ikt}$. For example, our estimates would be biased if high ability Asian students systemically select into classes assigned Asian TAs and high ability non-Asian students systematically select into classes assigned non-Asian TAs. Prior work looking at professor-student relationships potentially suffer from such selection biases, where students of a particular gender/race, and different academic capabilities, select into classes based on the teacher gender/race.[21]

To mitigate selection biases, previous studies have often focused on a subsample of students or classes where selection was arguably less of an issue.[22] Fortunately, in our setting, it is nearly impossible for undergraduates to identify which TAs are assigned to classes prior to enrollment. Importantly, the primary registration period for undergraduate classes occurs well before the Economics Department generates TA assignments for classes.[23] While undergraduates (technically) have the ability to register for courses after the end of the primary registration period, the majority of classes fill up by the time this period is over, leaving little capacity for students to be selective with course registration.

Table 2
Test for endogenous sorting.

	Full sample		Prof. survey sample	
	(1)	(2)	(3)	(4)
Outcome: Fraction TAs Asian				
Fraction of students Asian	−0.127	−0.159	0.086	0.108
	(0.225)	(0.228)	(0.330)	(0.333)
Avg. $\widehat{StudentGPA}$		1.441		1.049
		(1.623)		(2.732)
Avg. $\widehat{StudentGPA}$ × Fraction of students Asian		−3.198		−1.229
		(3.216)		(5.183)
Course and Term FE	X	X	X	X
R-squared	0.159	0.161	0.254	0.256
Observations	614	614	334	334

Notes: Each column presents results for a regression where the dependent variable is the fraction of the class's TAs that were Asian. Coefficients for term and course FE are not shown. The first column is a simple regression of the fraction of the class's TAs that were Asian on the fraction of the class's students that were Asian. The second column regresses TA race on (a) student race, (b) the average of the predicted values from a regression at the student-class level of the student's normalized GPA on a series of covariates from Table 1 (other than student race), and (c) an interaction between student race and the class' average predicted values. The next two columns repeat this analyses but for the sample of classes taught by professors who participated in our survey. Standard errors are in parentheses. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

To formally test for endogenous enrollment by race and ability, we collapse our data to the class level and estimate whether observable student characteristics correlate with the racial composition of the TAs in the class, conditional on course and term fixed effects. In the first column of Table 2, we consider a simple regression of the fraction Asian TAs on the percentage of students Asian. Next, we create an index of predicted ability from a cross sectional regression of grades on all of our individual-level covariates, except for TA and student race. In Column 2, we include the class average index and its' interaction with the percentage of students Asian. Finally, in Columns 3 and 4, we repeat this analysis while considering the subsample of classes taught by professors who completed our survey. Across all specifications, results in Table 2 show no evidence that student race or ability is predictive of TA race, with all the coefficients statistically insignificant and small in magnitude. Hence, the results from this analysis, coupled with practical knowledge of the registration process for students into classes, provide confidence that our primary regressor of interest is likely free from selection bias.[24]

4. Results

4.1. Main results

Table 3 presents our main results. “Effect of Similar Race” reports the estimated coefficient of interest ψ from specification Eq. (1). Recall

[19] For example, Asian students may be more likely to enroll in an international studies course and Asian TAs may be more likely to be assigned to international studies. Indeed, when evaluating student grades, our estimated magnitude of ψ slightly increases when we exclude course–by-race fixed effects (see Appendix Table A.7).

[20] There were 23 separate auditors who attended the discussion sections and office hours.

[21] Perhaps exacerbating selection biases in prior studies are services such as http://www.ratemyprofessor.com, which provide students with extensive information about their professors.

[22] For instance, Fairlie et al. (2014) focus on students with relatively low standing on registration priority lists since these students have little ability to be selective with their courses.

[23] For example, for the Spring 2014 term, which started in March, the primary undergraduate registration period started on February 3 and ended on February 14. The Economics Department generated and privately revealed TA assignments on February 27 to TAs and professors.

[24] We also consider additional tests of endogenous enrollment in the Appendix. First, in Table A.15, we expand on these regressions where we regress TA race on all our observables and interactions between student race and our observables. Second, we mimic the “sorting regressions” of Fairlie et al. (2014) in Table A.1, and find no evidence of endogenous sorting. The primary benefit of the Fairlie et al. (2014) specification is the ability to condition on class fixed effects. A drawback is that one cannot simultaneously test the importance of observables X_{ikt} in predicting TA race. Lastly, in Table A.2, we consider the same test as in Table A.15 but only using characteristics of students who completed the course; these results are very similar to those in Table A.15, highlighting how drop rates are low in our setting.

Table 3
Main results.

	Standardized grade				Passed class			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full sample								
Effect of Similar Race	0.078***	0.077***	0.076***	0.061**	0.017**	0.030***	0.020**	0.017**
[$Asian_i$ * $AsianTA_{ikt}$]	(0.025)	(0.021)	(0.024)	(0.025)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	57,718	49,177	57,718	57,718	59,121	50,329	59,121	59,121
Panel B: Professor survey sample								
Effect of Similar Race	0.080**	0.086**	0.079**	0.066*	0.014	0.025**	0.014	0.012
[$Asian_i$ * $AsianTA_{ikt}$]	(0.034)	(0.034)	(0.033)	(0.034)	(0.011)	(0.012)	(0.010)	(0.011)
Observations	33,997	29,262	33,997	33,997	34,751	29,885	34,751	34,751
Term FE			X	X			X	X
Course FE			X	X			X	X
Class FE	X	X			X	X		
Student FE		X				X		
Controls:								
Professor			X				X	
Student	X		X		X		X	
Student × Term	X	X	X		X	X	X	

Notes: "Effect of Similar Race" is Asian graduate TA composition interacted with an Asian student dummy. Standardized grade has a mean of zero and a standard deviation of one by class. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in economics, double major, class standing (Freshman/Sophomore/Junior/Senior), and professor gender and race. All specifications include course-by-race and term-by-race fixed effects. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

that ψ can be interpreted as the expected relative change in performance between Asian and non-Asian students when the student has all Asian TAs instead of all non-Asian TAs. We start in column (1) with our preferred specification of class fixed effects with student controls. We estimate a statistically significant coefficient of 0.078 for $Asian_i$ * $AsianTA_{ikt}$, which implies students do relatively better when matched to TAs of similar race. More specifically, we predict a 7.8% of a standard deviation increase in course grade when students are matched to TAs who are all of a similar race as themselves.[25] Given the standard deviation of course grades is slightly over one grade point unit, and the value of a grade modifier (+/−) is a third of a grade point unit, this effect is roughly equivalent to an increase of a fourth of a grade modifier.[26] For the remaining columns of Table 3 under "Standardized grade", we consider the sensitivity of the results to the inclusion of different fixed effects and controls. Most notably, in the second column, we replace student-level controls with student fixed effects.[27] Across all specifications, we estimate statistically significant gains for students when assigned TAs of similar race.[28] Standard errors are clustered by professor for all specifications.[29] Panel B presents the results for classes where the professor responded to our survey.[30]

The last four columns of Table 3 consider an indicator for whether the student passed the class as an outcome variables. Recall that "Passed class" is essentially just an indicator for whether the student received a letter grade of C− or higher. Consistent with the results for standardized grade, we again find positive racial interaction effects: (non-)Asian students experience increases in the likelihood of passing the class when assigned to (non-)Asian TAs. For our preferred model in column (5), we estimate a positive racial interaction effect of 1.7 percentage points, which is statistically significant at the 5%level. [31]

4.2. Specifications using letter grades

In order to test the robustness of our results further, and to understand how the distribution of grades shifts in response to TA race, we consider alternative specifications utilizing the raw letter grades students received in their classes. Students who enrolled in a class for a letter grade received either an A(−), B(+/−), C(+/−), D(+/−), or F. Fig. 1 displays the marginal effects from ordered logit regressions on the probability of attaining each possible letter grade. Similar to our main specification, "Effect of Similar Race" reports the coefficients on $Asian_i$ * $AsianTA_{ikt}$, while the remaining two sets of estimates report the marginal effects for Asian/non-Asian students in response to Asian/non-Asian TA racial composition, respectively.[32] We find that students are

[25] It's important to note that a positive racial interaction effect could arise if (non-)Asian students receive higher scores when taking a class with (non-)Asian TAs, or if, for example, all students irrespective of race do better with Asian TAs, but Asian students perform especially well relative to non-Asian students when matched to Asian TAs.

[26] Another way to interpret our results is to compare our coefficients to the professor quality literature. For a student who switches from having a class with no similarly-raced TAs to all similarly-raced TAs, our effect size is equivalent to raising professor quality by roughly a standard deviation (Rockoff, 2004; Carrell and West, 2010).

[27] Since student fixed effects rely on within student, across class variation, our primary regressors of interest are only identified with students who enrolled in more than one class.

[28] When the data are parsed by White and non-White students and TAs, this coefficient drops slightly to 0.076 standard deviations, and maintains statistical significance at the 1% level (see Appendix Table A.4). Racial interactions remain statistically significant when we consider specifications with finer race categorizations (see Appendix Tables A.5 and A.6).

[29] With fewer professor clusters than class clusters, we conservatively cluster at the professor level instead of the class level. Moreover, clustering at the professor level makes sense since professors ultimately determine students' grades. Ideally, we would cluster at the TA level, but since a single class may contain up to three TAs, a single observation may belong to up to three TA clusters. There are fewer professors than TAs in our setting. As a robustness check, we consider the subsample of classes which had only one TA and cluster at the TA level. Both estimated magnitudes and standard errors slightly increase, with the results remaining largely statistically significant (see Appendix Table A.7, Panel C). In general, standard errors decrease when we cluster at the class level instead of professor level.

(*footnote continued*)

[30] Panels A and B of Appendix Table A.7 investigate the sensitivity of the results to further combinations of controls and fixed effects for the main sample and professor survey sample, respectively.

[31] One hypothesis for these main results is that the racial interaction effects simply reflect a systematic change in student composition that occurs after students enroll in the class. That is, after students observe the race of their TAs, they decide whether to drop the course. While this effect is likely to be small, since overall drop rates are under 2% (Table 1), we formally test for this possibility using "Dropped class" as an outcome variable in Appendix Table A.8. We find a very small, positive, and statistically insignificant racial interaction effects, suggesting, if anything, that students are slightly *more* likely to drop a class with TAs of similar race.

[32] Appendix Table A.9 reports the estimated coefficients and marginal effects from these regressions, as well as estimates from ordered probit models. Estimates across

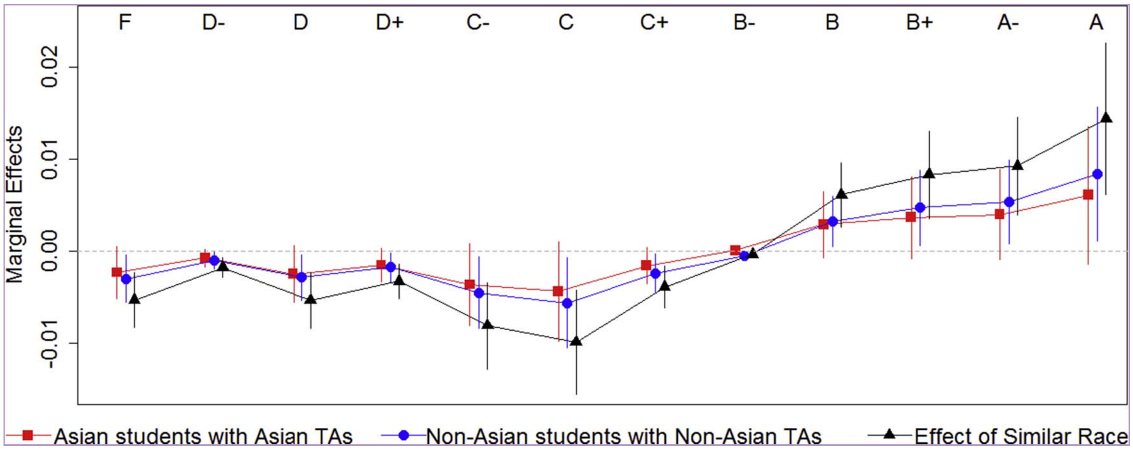

Fig. 1. Marginal effects of TA race on letter grades. Notes: Each of the three connected lines present marginal effects from an ordered logit regression of having TAs of similar race (or for "Effect of Similar Race", $Asian_i * AsianTA_{ikt}$) on the probability of attaining each possible letter grade. Coefficients are reported in Appendix Table A.9. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in the subject of the course, double major, class standing (Freshman/Sophomore/Junior/Senior), and professor gender and race. Standard errors are clustered by professor. 95% confidence intervals plotted for each estimated marginal effect.

Table 4
Audit study of TA section and office hour attendance.

	Discussion section			Office hours			Pooled	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: % Students Asian								
Hosted by Asian TA	0.076**	0.085*	0.084*	0.330***	0.134	0.200*	0.081*	0.081**
	(0.034)	(0.044)	(0.045)	(0.120)	(0.124)	(0.103)	(0.045)	(0.038)
Observations		118			43		161	
Mean of outcome		0.576			0.622		0.588	
Controls		X	X		X	X	X	X
Weighted observations			X			X		X

Notes: Each cell reports the coefficient on an indicator for whether the TA for the discussion section or office hour was Asian. The outcome variable is the fraction of attended students who were Asian. Controls include indicators for day of the week, time slot, and auditor. Weights reflect total attendance of the discussion section or office hour. Robust standard errors are presented in parenthesis. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

significantly more likely to attain grades of B or higher when matched to TAs of similar race. Correspondingly, students are also less likely to attain grades of C+ or lower when matched to TAs of similar race. The largest marginal effects come from increases in the probability of receiving an A, followed by decreases in the probability of receiving a C, in response to having TAs of similar race.

4.3. Audit study of TA section and office hour attendance

Next, we turn to the Spring 2015 audit study to test for student response to TA race by examining student attendance at optional TA discussion sections and office hours. Results in Table 4 show that across all variations of specification Eq. (2) and samples, TA race is positively related to the race of the attending students. For example, we predict an 8.4 (column 3) and 20.0 (column 6) percentage point increase in the fraction of Asian students attending discussion section and office hours, respectively, when taught by an Asian TA.[33] Given the lack of association between student race and TA race in student enrollment from Table 2, correlations in race at TA discussion sections and office hours can only occur if within each class, attendance is shifting across discussion sections and office hours to match their TA's race.[34] More precisely, students are either rearranging themselves across discussion sections and office hours to increase racial match, and/or students are simply more likely to attend their own TA's discussion sections and office hours when they share the same race as their TA.

4.4. Professor survey samples

We now turn to the professor survey portion of our main sample to examine whether our racial interaction effects differ across classes based on the professors' responses. These results are presented in Table 5, where we consider our main specification with class fixed effects and a full set of controls.[35] Responses to both of the two questions on the professor survey appear to determine which classes are driving the racial interaction effects. First, we find that the effects are particularly driven by classes where TAs were given advanced copies of the exam, where we estimate a racial interaction effect of 0.127; meanwhile, in classes where the exams were not shared with TAs, we estimate a statistically insignificant −0.003 racial interaction effect. We also find that the effects are largest in classes with non-multiple choice

(*footnote continued*)
ordered logit and ordered probit specifications are nearly identical and exhibit similar patterns.

[33] From Appendix Table A.14, we also see that the total number of (White) Asian students who attend TA sections and office hours increases when the TA is (White) Asian.

[34] This is assuming enrollment patterns in Spring 2015 reflect the lack of endogenous enrollment from our main results, which utilize data from 2003 to 2011 and condition on term and course fixed effects.

[35] Table A.10 presents professor survey results across a variety of alternate specifications.

Table 5
Professor survey results.

		Exams shared w/TAs?		Multiple choice exams?	
	All	No	Yes	No	Yes
Outcome: Standardized grade					
Effect of Similar Race	0.080**	−0.003	0.127**	0.199***	0.046
[$Asian_i * AsianTA_{ikt}$]	(0.036)	(0.048)	(0.055)	(0.042)	(0.056)
Observations	33,946	9189	19,119	9185	24,290
Class FE	X	X	X	X	X
Controls:					
Professor					
Student	X	X	X	X	X
Student × Term	X	X	X	X	X

Notes: Standardized grade has a mean of zero and a standard deviation of one by class. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in economics, double major, class standing (Freshman/Sophomore/Junior/Senior), and professor gender and race. All specifications include course-by-race and term-by-race fixed effects. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table 6
Specifications with future and past TA race — outcome: standardized grade.

	Full sample						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Future TAs							
$Asian_i \times AsianTA_{ikt}$	0.062*	0.114***	0.086***	0.116***	0.122***	0.078***	0.128***
	(0.034)	(0.028)	(0.030)	(0.028)	(0.027)	(0.024)	(0.025)
$Asian_i \times AsianTA_{i(t+1)}$	−0.006	0.017	0.015	0.010	0.030	0.019	0.020
	(0.030)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Observations	36,294	36,294	36,294	36,294	36,294	36,294	36,294
Panel B: Past TAs							
$Asian_i \times AsianTA_{ikt}$	0.116***	0.141***	0.122***	0.139***	0.123***	0.097***	0.122***
	(0.026)	(0.025)	(0.026)	(0.025)	(0.025)	(0.022)	(0.023)
$Asian_i \times AsianTA_{i(t-1)}$	−0.012	−0.014	−0.005	−0.020	−0.005	0.005	0.006
	(0.029)	(0.026)	(0.028)	(0.027)	(0.030)	(0.031)	(0.030)
Observations	37,214	37,214	37,214	37,214	37,214	37,214	37,214
	Sequence courses						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel C: Next course TAs							
$Asian_i \times AsianTA_{ikt}$	−0.036	0.013	−0.009	−0.003	0.069	0.025	0.031
	(0.087)	(0.074)	(0.075)	(0.078)	(0.116)	(0.113)	(0.114)
$Asian_i \times AsianTA_{next.course}$	−0.127*	0.003	−0.027	0.013	−0.001	0.042	0.050
	(0.071)	(0.051)	(0.054)	(0.050)	(0.084)	(0.114)	(0.077)
Observations	8381	8381	8381	8381	8381	8381	8381
Panel D: Prior course TAs							
$Asian_i \times AsianTA_{ikt}$	0.162*	0.157**	0.145*	0.161**	0.071	−0.018	0.099
	(0.081)	(0.067)	(0.074)	(0.064)	(0.100)	(0.117)	(0.106)
$Asian_i \times AsianTA_{prev.course}$	0.106*	0.089*	0.118**	0.082	0.113	0.114	0.108
	(0.057)	(0.047)	(0.050)	(0.050)	(0.090)	(0.089)	(0.097)
Observations	7429	7429	7429	7429	7429	7429	7429
Term FE	X		X			X	
Course FE	X		X			X	
Class FE				X			X
Student FE					X	X	X
Controls:							
Professor		X	X				
Student		X	X	X			
Student × Term		X	X	X			

Notes: In Panels A and B, the sample includes students who enrolled in at least two terms of economics courses. In Panels C and D, the sample includes students who enrolled in the second course in of a two-course series for students who enrolled in the entirety of the two-course series. There are a total of nine two-course series that appear in our data: (Introductory/ Intermediate) Microeconomics, (Introductory/Intermediate) Macroeconomics, (Introductory/Intermediate) Econometrics, Industrial Organization (A/B), Labor Economics (A/B), World Economic History (A/B), US Economic History (A/B), International Economics (A/B), and Public Economics (A/B). Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

exams (0.199), while we observe smaller, statistically insignificant interaction effects when focusing on classes that had exams with multiple choice (0.046).[36]

We interpret these first results as TAs "teaching to the test", where when a TA is given a copy of the exam, the TA adjusts his/her discussion section and office hour lessons to better suit the material that will appear on the exam. Teaching to the test would benefit students who attend discussion sections and office hours, and as suggested by the audit study, attending students tend to be of similar race as the TA. We posit that the latter results by classes with multiple choice exams could be driven by several explanations. First, it could be that classes without multiple choice exams may require more critical thinking skills, which are gained in TA discussion sections and office hours. Another explanation stems from TA grading behavior, since classes with non-multiple choice exams allow TAs to exercise more subjective judgments when grading. Additionally, students of specific races may be more likely to answer non-multiple choice questions in a manner which TAs of a similar race favor. We return to these results in Section 5 when we further discuss potential mechanisms underlining the racial interaction effects in conjunction with results in the next two sections.

4.5. Specifications with past and future TA race interactions

In this section, we consider our main specification while including an additional regressor of interest: student race interacted with the student's TA racial composition from previous or future courses. Examining if student performance in current courses responds to TA race in *future* courses serves as an additional validity check of our identification strategy. Under the assumption that there are no across-term correlations of selection into courses by TA race, the race of a student's TAs in future courses should have no influence on a student's current term performance. Panel A of Table 6 presents these results, where the additional regressor is ($Asian_i \times AsianTA_{i(t+1)}$). Across all specifications, we find that the race of future TAs has no impact on current term performance.[37]

Regressions where we interact student race with the student's past TA race test for potential spillover effects. If material across courses had significant overlap and there were significant increases in learning in response to TA race, then the racial composition of a student's *past* TAs would influence their current grades. To test for this possibility, we again consider our main specification where we additionally include an interaction term between the indicator for student race $Asian_i$ and the proportion of student *i*'s TAs who were Asian in the term prior to the class being taken.

In Panel B of Table 6, results for the full sample show no evidence that the racial composition of a student's prior TAs influences current grades. However, in Panels C and D of Table 6, we instead focus on the set of "sequenced" economics courses. Within the Economics Department in our setting there are nine two-course sequences where either the first course is a prerequisite for the second course, or the courses come from the same subfield within economics.[38] We do so because these are courses for which a test for positive spillovers is likely more appropriate, particularly since material across these two courses should have significant overlap. In Panel C, the additional regressor included is an interaction between student race and the TA racial composition from the student's second course in the two-course sequence ($AsianTA_{next.course}$); this again serves as a placebo test, since the race of future TAs should have no impact on present course outcomes. In Panel D, student race is interacted with TA racial composition from the first course in the two-course sequence ($AsianTA_{prev.course}$), which presents a test of spillovers.[39] From Panel C, we again find that future TA race has no impact on student grades. Panel D provides some evidence of positive spillovers. Though we only attain statistical significance at the 10% level in three of seven specifications, we find lagged interaction effects ranging between 0.081 and 0.118. In total, and discussed in further detail later in the paper, we interpret these results as suggestive evidence of increased learning and human capital accumulation for students when matched to TAs of similar race.

4.6. Subsequent course enrollment and major choice

Lastly, we return to our main specification, with class fixed effects and our full set of controls, to explore whether there are persistent racial matching effects in the form of student decisions to enroll in more economics courses and to major in economics. We define "Enroll in another class " as a student-class level indicator for whether the student enrolled in another economics class in a later term, and "Major in Economics" as a student-level variable that indicates whether the student was declared as an economics major during their last Economics class at the university.[40]

Table 7 presents these results. For our full sample, we find positive, but statistically insignificant, racial interaction effects on course enrollment (0.008) and majoring (0.007). To explore differences across subsamples, we estimate a triple interaction of $Asian_i$ * $AsianTA_{ikt}$ with an indicator for the subsample of interest. From these models, we start to see more convincing evidence of persistent effects. For instance, in response to racial match, the likelihood of enrolling in another class for Freshmen and Sophomores (i.e. "lower classmen") is over twice the size of the response for upper classmen. Freshmen and Sophomores are also statistically significantly more likely to major in economics in response to racial match. We also find a stronger racial matching effect for subsequent enrollment in classes where exams were shared with TAs, and where exams were not multiple choice, which, unsurprisingly, mirrors the observed boosts in contemporaneously grades in the professor survey sample. Though statistically insignificant, we also find non-economics majors, relative to economics majors, are much more likely to enroll in another economics class in response to racial match. Relative to students in advanced classes, students in introductory economics courses are more likely to major in economics in response to racial match. Finally, we find some evidence that the racial interaction effects had particularly positive persistent effects on first generation college-going students: these students were 1.2 percentage points more likely to enroll in another economics class and 2.7 percentage points more likely to major in economics after taking a class with TAs of similar race.

[36] We also find that the racial interaction effects are strongest in classes that had both shared exams with TAs and no multiple choice (see Appendix Table A.11).

[37] Future race is calculated by taking the average TA racial composition across a student's economics classes in the subsequent term of classes enrolled. Note that this analysis drops all students who only enrolled in one term of classes, and the last term for which students enrolled in classes.

[38] These two-course sequences include (Introductory/Intermediate) Microeconomics, (Introductory/Intermediate) Macroeconomics, (Introductory/Intermediate) Econometrics, Industrial Organization (A/B), Labor Economics (A/B), World Economic History (A/B), US Economic History (A/B), International Economics (A/B), and Public Economics (A/B).

[39] This analysis suffers from significantly reduced statistical power, particularly since our sample is reduced to the focus on students who enrolled, at least once, in both courses of a two-course sequence.

[40] Unfortunately, we can only observe a student's declared major at the time they enrolled in the course. Thus, we cannot observe any instance where a student switched their major after their final economics course at the university. For example, any incoming students declared as economics majors who subsequently enrolled in an introductory economics class and experienced a negative outcome with dissimilarly-raced TAs may have decided to switch out of the economics major and refrain from enrolling in another economics course. To account for this, we coded any students who were declared as an economics major as not finishing with an economics major if they did not enroll in any classes beyond the two introductory courses.

Table 7
Main results for enrollment in another economics class and major in economics.

		Subsample				
	Full sample	Lower classman	Non-Econ. major	First gen.	Shared exams	No MC
Enroll in another class						
Effect of Similar Race	0.008	0.006	0.004	0.007	0.021	0.021
[$Asian_i * AsianTA_{ikt}$]	(0.010)	(0.010)	(0.010)	(0.012)	(0.020)	(0.020)
Triple interaction		0.007	0.010	0.005	0.006	0.012
[$Asian_i * AsianTA_{ikt} *\mathbb{1}(Sample)$]		(0.020)	(0.020)	(0.019)	(0.026)	(0.026)
Observations	60,642	60,642	60,642	60,642	29,668	35,088
	Full sample	Lower classman	Intro course	First gen.	Shared exams	No MC
Major in Economics						
Effect of Similar Race	0.007	−0.004	0.005	−0.001	0.014	−0.014
[$Asian_i * AsianTA_{ikt}$]	(0.009)	(0.010)	(0.010)	(0.012)	(0.018)	(0.019)
Triple interaction		0.039*	0.010	0.028	−0.029	−0.022
[$Asian_i * AsianTA_{ikt} *\mathbb{1}(Sample)$]		(0.022)	(0.026)	(0.018)	(0.025)	(0.026)
Class FE	X	X	X	X	X	X
Controls:						
Professor						
Student	X	X	X	X	X	X
Student × Term	X	X	X	X	X	X
Observations	60,642	60,642	60,642	60,642	29,668	35,088

Notes: "Effect of Similar Race" is Asian graduate TA composition interacted with an Asian student dummy. "X Indicator for Header" is a triple interaction between "Effect of Similar Race" and an indicator variable for the label in the header. "Lower classman" are those who are flagged as being a Freshman or Sophomore. "First gen." are first generation college students. "Enroll in another class" is an indicator for whether the student enrolled in another class in a future term. "Major in Economics" is an indicator for whether the student "finished" with an economics major. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in economics, double major, and class standing (Freshman/Sophomore/Junior/Senior). All specifications include course-by-race and term-by-race fixed effects. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

5. Discussion

5.1. Potential mechanisms

An important question to address for welfare and potential policy implications centers on the mechanisms that are driving our results. TA race could influence student outcomes in several manners. Role model effects are often mentioned as a determinant affecting educational outcomes. In our setting, students may be inspired by their TAs, or be more comfortable approaching and learning from their TAs due to the TA sharing a similar race.

Another channel is a match quality effect, where TAs of different race/ethnicity have particular teaching styles which are better suited to students of similar race/ethnicity. Included in this channel is a language matching effect, where students learn more if course material can be explained in the student's native language, which is more likely to occur when students share the same race/ethnicity as their TAs. Thus, with a match quality effect, students and TAs are not directly responding to the other's race, but instead students are reacting to a characteristic that is, on average, associated with their TAs' race/ethnicity.

Finally, TAs could exhibit bias with respect to how they treat students of a similar race. Discrimination could happen on an unconscious level where, for example, TAs of particular races may be more lenient when grading certain types of errors on exams that are more likely to be made by students of similar race. Such "grade inflation" could still lead to subsequent learning and human capital gains through a type of "self-signaling" model (e.g., Dee et al., 2016; Diamond and Persson, 2016).

Though we cannot rule out potential TA biases, we believe our results to be most consistent with role model effects and match quality effects. To start, the audit study provides direct evidence of students responding to the TA race in the form of voluntary attendance. Furthermore, the underlying motive for the students' attendance could be driven by a match quality effect, where a student is learning more from their TAs due to the TAs' teaching styles or capabilities; this is particularly so given that the audit study started during the third week of school, when students are unlikely to know much about their TAs beyond their superficial characteristics. We also find the racial matching effects to be strongest in classes where exams were shared with TAs; we believe this to be evidence of "teaching to the test", and students of similar race as the TA particularly benefit from the TA "teaching to the test" since similarly-raced students are more likely to attend the TA's discussion sections and office hours. "Teaching to the test", independent of attendance differences, could only explain our racial matching effects if TAs had shared differential exam information to students by race; though we cannot formally rule this out, we find it unlikely to be a significant driver. The strongest piece of evidence for potential TA biases lies in the stronger effects in classes without multiple choice exams; it could be that students of specific races may be more likely to answer non-multiple choice questions in a manner which TAs of a similar race favor.[41] Of course, it could also be that classes that rely less on multiple choice exams are classes where student-TA relationships are generally more important for learning the material and succeeding in the class.

Lastly, the persistent effects from racial matching are perhaps the most convincing pieces of evidence of significant learning and human capital gains driven by role model effects and match quality gains. The only feasible channel through which grading biases could lead to a persistent student response is discussed and identified in recent work from Diamond and Persson (2016) and Dee et al. (2016); these papers find that "grade inflation" (giving higher scores than those earned based on performance) led to boosts in subsequent student performance. In our setting, it could be that students' grades are inflated in response to TA bias, which then serves as a type of self-signal for the student, which subsequently positively influences their decisions about enrollment and effort in future economics courses. We believe, however, that this channel is unlikely to apply to our setting, namely because we only find increased subsequent performance for "sequenced

[41] For example, perhaps Asian TAs are more likely to be forgiving of an answer written with poor grammar, and perhaps Asian students are more likely to write with poor grammar.

courses", or courses which had significant overlapping material. To argue a self-signaling model, Diamond and Persson (2016) show that test score inflation led to boosts in subsequent performance in *other, unrelated* subjects. In our setting, if one were to assume that the finest level with which grade inflation boosts a students' belief is in economics overall, then we should see improvements in subsequent performance across all economics courses, which is not the case in our setting (Panel B of Table 6). In total, it appears biases in grading could, at most, explain only a small part of the effects, while role model effects and match quality gains are likely the biggest drivers.

5.2. Policy implications

Though we find robust evidence of gains to racial matching, the potential policy implications are not necessarily straightforward. Even in the case where racial matching effects were strictly driven by increases in student effort and learning, student-TA racial matching effects could still exist in a setting where all students, irrespective of race, perform better in response to a particular race. For instance, it could be that all students see boosts in performance in response to having Asian TAs, but that the boost is larger for Asian students. Hence, one would face an efficiency-equity tradeoff if one were to consider sorting of TAs/students to maximize racial matching; namely, students who share a race with TAs of overall lower quality would miss out.

If it was instead the case that all students see boosts in performance when matched to similarly-raced TAs, then the department/university could consider sorting TAs to maximize racial match and improve performance for all students. Though our identification strategy exploits variation in racial match within classrooms, we can investigate improvements in overall efficiency due to natural racial composition match between students and TAs. In Appendix Tables A.13 and A.14, we collapse our data to the class level and regress class-level outcome variables on an interaction between the fraction of students who were Asian and the fraction of TAs who were Asian. Indeed, we find that classes with greater racial composition match had higher average GPAs, passing rates, and attendance rates overall. Thus, on an intensive margin, university administrators could aim to arrange their TAs across classes to match the racial composition of students.

Another potential policy margin of interest is on the employment of TAs. On the "extensive" margin, departments could increase the employment of TAs to better match the racial composition of the student body, thus increasing the overall likelihood of a racial match. More generally, although our setting focuses on an Asian vs. non-Asian split, our results have implications toward policies aimed at expanding minority representation of instructors. A frequently debated policy prescription for mitigating racial achievement gaps centers on increasing the number of minority faculty to serve as role models for minority students. As such, our results support this notion, where we would expect to see improvements in student outcomes if, all else equal, there were shifts in the employment of instructors to better reflect the racial composition of the undergraduate student population.

6. Conclusions

In spite of increases in overall attendance, college completion rates have stagnated in the US. A natural question to ask is, once the student enters college, what factors determine student success? The goal of this paper is to shed light on the importance of TAs in determining student outcomes, focusing on the role of TA race. Understanding how TA race influences student outcomes is especially important given recent trends in the US, where the racial composition of undergraduate and graduate programs have been experiencing dramatic shifts over the past 40 years. Much of this shift can be attributed to large influxes from abroad, particularly from Asian countries.

Our primary analyses come from detailed student administrative data from a large public university in California, paired with TA assignment data from the university's Department of Economics. To overcome concerns of potential selection bias, we first focus on models with class fixed effects, where we compare differences in outcomes between students across different races when assigned to the same TAs within the same class. Additionally, we simultaneously control for sorting that occurs across classes by including student fixed effects. We find no evidence of endogenous sorting into classes by student race when predicting the race of the class' TAs with a full set of controls. The lack of sorting is unsurprising since students have very little ability identifying which classes TAs are assigned to, and TA assignments are generated after the undergraduates' primary registration period ends.

Using Asian vs. non-Asian groupings, we find that students perform better when taking a class with TAs who are of a similar race. Students are more likely to attend their TA's optional office hours and discussion sections when the TA is of a similar race. Racial interactions are strongest in classes where TAs had been given a copy of the exam prior to the exam date, and when the exams for the class had no multiple choice. We also find suggestive evidence of persistent effects in the form of subsequent course performance, course enrollment, and majoring choice. Performance in the second course of a two-course sequence is improved when the student was racially matched to TAs in the first course. Lastly, Freshmen and Sophomores are more likely to enroll in another economics class, and major in economics, after taking a class with similarly-raced TAs. Overall, we find evidence of student learning and human capital accumulation in response to TAs that can primarily be attributed to role model effects (students responding to TAs of similar race) and match quality gains (TAs teaching style or capabilities better match students of similar race).

Appendix A. Results Appendix

"Sorting Regressions" from Fairlie et al. (2014):

$$\overline{X}_{ac} = \delta_1 AsianTA_c + \delta_2 I_a + \delta_3 AsianTA_c {}^* I_a + v_{ac}. \tag{3}$$

Table A.1
Sorting regressions — Fairlie et al. (2014) (AER).

	High school							
	Female	GPA	Age	Admit as transfer	# Prior units	Double major	International	Class major
Full sample	0.014	−0.018	−0.024	0.007	−1.537	−0.014	−0.000	0.003
	(0.018)	(0.014)	(0.061)	(0.015)	(1.924)	(0.018)	(0.012)	(0.017)
Professor survey subsample	0.013	−0.001	−0.065	0.008	−1.759	−0.008	0.009	−0.009
	(0.023)	(0.016)	(0.087)	(0.022)	(2.934)	(0.027)	(0.018)	(0.022)

Classes with one TA	0.005	−0.019	−0.060	−0.007	−1.390	−0.011	−0.003	0.002
	(0.024)	(0.019)	(0.071)	(0.020)	(2.424)	(0.024)	(0.016)	(0.021)
Class FE	X	X	X	X	X	X	X	X

Notes: Each cell displays results from a regression of the race-specific average student outcomes in a classroom on an indicator for whether the average is associated with Asian students, the fraction of the TAs assigned to the class who are Asian, the interaction between these two variables, and class fixed effects. This table reports the coefficient on the interaction term, which can be interpreted as the extent to which Asian students sort into classes assigned Asian TAs. Outcomes for each regression vary across columns. Rows are defined by the subsample of students we consider. Students and TAs are classified as Asian if their primary race is recorded as Chinese, Japanese, Korean, Filipino, South-East Asian, Vietnamese, Thai, or "Other Asian". Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.2
Regression of TA race on observables — sample of students who completed course.

	Full sample		Prof. survey sample	
	(1)	(2)	(3)	(4)
Outcome: Fraction TAs Asian				
Fraction of students Asian	−0.001	–	0.301	–
	(0.263)	–	(0.395)	–
Fraction of student female	−0.299	−1.457	−0.598	−1.199
	(0.274)	(1.061)	(0.418)	(1.798)
Fraction of students admitted as transfer	1.152**	−2.221	1.266*	−4.090
	(0.517)	(1.855)	(0.735)	(3.186)
Average age of students	−0.113	0.174	−0.060	0.346
	(0.101)	(0.296)	(0.154)	(0.458)
Fraction of students international	0.094	2.492	−0.201	1.320
	(0.522)	(2.185)	(0.687)	(3.373)
Fraction of students first generation	−0.529*	−0.606	−0.962**	−3.264
	(0.318)	(1.263)	(0.458)	(2.369)
Average high school GPA of students	0.045	−1.745	0.296	−2.121
	(0.414)	(2.031)	(0.597)	(3.096)
Average admission year	0.049	−0.000	0.538	0.570
	(0.347)	(0.355)	(0.483)	(0.510)
Fraction of student Econ major	−0.134	0.737	−0.152	3.382**
	(0.272)	(0.869)	(0.411)	(1.621)
Fraction of students double major	−0.171	0.458	0.200	−1.190
	(0.393)	(1.479)	(0.584)	(2.818)
Average # of units up to class	0.008	−0.012	0.017	−0.012
	(0.008)	(0.013)	(0.010)	(0.022)
Female professor	−0.060	−0.133	−0.083	−0.082
	(0.048)	(0.211)	(0.071)	(0.371)
Asian professor	0.107*	0.003	0.151	−0.041
	(0.056)	(0.284)	(0.099)	(0.670)
Fraction Asian × Fraction female		2.204		0.944
		(2.041)		(3.403)
Fraction Asian × Fraction admit as transfer		6.817*		10.947*
		(3.594)		(6.152)
Fraction Asian × Average age		−0.572		−0.774
		(0.543)		(0.850)
Fraction Asian × Fraction international		−4.359		−3.389
		(3.771)		(6.012)
Fraction Asian × Fraction first generation		0.153		4.594
		(2.434)		(4.476)
Fraction Asian × Average high school GPA		3.604		4.974
		(4.044)		(5.986)
Fraction Asian × Average admission year		−0.013		−0.169
		(0.102)		(0.176)
Fraction Asian × Fraction same major as class		−1.821		−6.873**
		(1.718)		(3.081)
Fraction Asian × Fraction double major		−1.179		2.771
		(2.887)		(5.187)
Fraction Asian × Average # of units up to class		0.037*		0.058*
		(0.022)		(0.034)
Fraction Asian × Female professor		0.163		0.013
		(0.420)		(0.716)

Fraction Asian × Asian professor		0.213		0.410
		(0.570)		(1.361)
Course & Term FE	Yes	Yes	Yes	Yes
P-value: Joint significance	0.219	0.606	0.315	0.422
R-squared	0.184	0.193	0.294	0.323
Observations	614	614	334	334

Notes: Each column presents results for a regression where the dependent variable is the fraction of the class's TAs that were Asian. Coefficients for term and course FE are not shown. *P*-value for joint significance of all individual covariates, conditional on term and course FE, included. The first column includes all baseline characteristics for the class. The second column includes interactions of the fraction of students who were Asian in the class with the baseline characteristics for the class. The next two columns repeat this analyses but for the sample of classes taught by professors who participated in our survey. Standard errors are in parentheses. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.3
Tests for sorting — regression of TA race on observables — student-class data.

	Full sample			Prof. survey sample		
	All students	Asian	Non-Asian	All	Asian	Non-Asian
Outcome: Fraction TAs Asian						
Asian student	0.001	–	–	0.002	–	–
	(0.004)	–	–	(0.004)	–	–
Female student	0.001	0.003	−0.003	−0.001	0.005	−0.006
	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Admit as transfer	0.016**	0.023*	0.013	0.011	0.023	0.004
	(0.008)	(0.012)	(0.011)	(0.010)	(0.015)	(0.013)
Age	−0.001	−0.002	0.001	0.001	−0.002	0.002
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
International student	−0.011	−0.009	−0.014	−0.014	−0.009	−0.030
	(0.010)	(0.010)	(0.018)	(0.010)	(0.011)	(0.021)
First generation	−0.003	−0.002	−0.004	−0.005	−0.004	−0.006
	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)
High school GPA	0.004	−0.006	0.013**	0.003	−0.001	0.008
	(0.005)	(0.008)	(0.006)	(0.007)	(0.009)	(0.008)
Admission year	−0.005	−0.004	−0.007	−0.001	−0.003	−0.001
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Same major as class	0.001	0.002	−0.003	0.001	−0.001	−0.001
	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Double major	0.001	0.001	0.001	0.007	0.005	0.010
	(0.007)	(0.010)	(0.009)	(0.009)	(0.011)	(0.011)
Freshman	0.002	−0.010	0.012	−0.001	−0.015	0.012
	(0.010)	(0.014)	(0.012)	(0.013)	(0.016)	(0.015)
Sophomore	0.008	0.005	0.009	0.002	−0.001	0.007
	(0.007)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)
Junior	0.001	0.001	0.003	−0.002	−0.010	0.007
	(0.006)	(0.008)	(0.007)	(0.008)	(0.010)	(0.008)
Female professor	−0.056	−0.057	−0.056	−0.031	−0.047	−0.016
	(0.042)	(0.041)	(0.044)	(0.059)	(0.058)	(0.061)
Asian professor	0.054	0.046	0.061	0.093	0.081	0.107
	(0.047)	(0.047)	(0.049)	(0.071)	(0.073)	(0.071)
Course & Term FE	Yes	Yes	Yes	Yes	Yes	Yes
P-value: Joint significance	0.706	0.421	0.389	0.891	0.540	0.592
R-squared	0.220	0.235	0.209	0.306	0.311	0.306
Observations	60,642	29,391	31,251	35,023	17,448	17,575

Notes: Each specification presents results for a regression where the dependent variable is the fraction of the student's TAs in the class that were Asian. Coefficients for term and course FE are not shown. *P*-value for joint significance of all individual covariates, conditional on term and course FE, included. The first column is our full sample. The next two columns consider Asian and non-Asian student subsamples. The final three columns pertain to the sample of classes taught by professors who participated in our survey. Standard errors are in parentheses, clustered by class. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.4
Main results by White vs. non-White.

	Standardized grade				Passed class			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full sample								
Fraction TAs White	−0.031***	−0.029***	–	–	−0.003	−0.002	–	–
	(0.010)	(0.011)	–	–	(0.007)	(0.007)	–	–
Effect of Similar Race	0.111***	0.104***	0.107***	0.076***	0.022***	0.021**	0.020**	0.022***
[$White_i$ * $WhiteTA_{ikt}$]	(0.026)	(0.024)	(0.024)	(0.021)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	57,718	57,718	57,718	49,177	59,121	59,121	59,121	50,329
Panel B: Professor survey sample								
Fraction TAs White	−0.041***	−0.038**	–	–	−0.010	−0.008	–	–
	(0.014)	(0.015)	–	–	(0.009)	(0.009)	–	–
Effect of Similar Race	0.119***	0.109***	0.114***	0.072**	0.024**	0.021**	0.023**	0.026**
[$White_i$ * $WhiteTA_{ikt}$]	(0.035)	(0.032)	(0.033)	(0.032)	(0.010)	(0.010)	(0.010)	(0.011)
Observations	33,997	33,997	33,997	29,262	34,751	34,751	34,751	29,885
Term FE	X	X			X	X		
Course FE	X	X			X	X		
Class FE			X	X			X	X
Student FE				X				X
Controls:								
Professor		X				X		
Student		X	X			X	X	
Student × Term		X	X	X		X	X	X

Notes: "Effect of Similar Race" is White graduate TA composition interacted with a White student dummy. Standardized grade has a mean of zero and a standard deviation of one by class. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in economics, double major, class standing (Freshman/Sophomore/Junior/Senior), and professor gender and race. All specifications include course-by-race and term-by-race fixed effects. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.5
Estimated role of TA race for student outcomes — group by group regressions.

	Outcome: Standardized grade				Outcome: Passed class			
	Racial composition of TAs (comparison group: own race TA)				*Racial composition of TAs (comparison group: own race TA)*			
	White	Chinese	*Other Asian*	*Hispanic (Other)*	*White*	Chinese	*Other Asian*	*Hispanic (Other)*
White	–	−0.078***	−0.081***	−0.041	–	−0.016*	−0.022***	−0.018
	–	(0.017)	(0.022)	(0.032)	–	(0.008)	(0.008)	(0.012)
Chinese	−0.073***	–	−0.008	−0.027	−0.014	–	0.004	−0.022
	(0.024)	–	(0.022)	(0.040)	(0.009)	–	(0.009)	(0.017)
Other Asian	−0.008	−0.034	–	0.064	0.003	−0.012	–	0.017
	(0.032)	(0.030)	–	(0.049)	(0.012)	(0.013)	–	(0.024)
Hispanic (Other)	0.009	0.043	0.003	–	−0.012	−0.022	−0.009	–
	(0.052)	(0.050)	(0.059)	–	(0.021)	(0.019)	(0.022)	–

Notes: This table displays results from regressions that are run separately for each student race. Each cell reports the coefficient for TA racial composition. Standardized grade has a mean of zero and a standard deviation of one. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in the subject of the course, double major, class standing (Freshman/Sophomore/Junior/Senior), and professor gender and race. Course and term fixed effects included. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.6
Full model with multiple same race interactions.

	Standardized grade						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Chinese_i \times ChineseTA_{ikt}$	0.051	0.063**	0.065**	0.067**	0.072***	0.076***	0.084***
	(0.038)	(0.031)	(0.030)	(0.031)	(0.025)	(0.025)	(0.027)
$OtherAsian_i \times OtherAsianTA_{ikt}$	0.032	0.056	0.053	0.053	0.016	0.021	0.017

	(0.038)	(0.035)	(0.035)	(0.035)	(0.031)	(0.030)	(0.029)
$White_i \times WhiteTA_{ikt}$	0.094***	0.114***	0.105***	0.107***	0.089***	0.086***	0.086***
	(0.029)	(0.026)	(0.026)	(0.027)	(0.022)	(0.020)	(0.021)
Observations	57,718	57,718	57,718	57,718	49,177	49,177	49,177
Term FE	X		X			X	
Course FE	X		X			X	
Class FE				X			X
Student FE					X	X	X
Controls:							
Professor		X	X				
Student		X	X	X			
Student × Term		X	X	X			

Notes: Each cell reports the coefficient on the interaction between a student race identifier and the fraction of TAs who were of similar race. For each regression, covariates for students/TAs of "Other" race are omitted. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in the subject of the course, double major, and class standing (Freshman/Sophomore/Junior/Senior). Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.7
Robustness checks — additional specifications with standardized grade.

	Standardized grade						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Full sample							
Fraction TAs Asian	−0.037**	−0.079***	−0.045***	–	−0.132***	−0.040**	–
	(0.014)	(0.015)	(0.014)	–	(0.017)	(0.016)	–
Effect of Similar Race	0.061**	0.098***	0.076***	0.096***	0.113***	0.074***	0.116***
[$Asian_i$ * $AsianTA_{ikt}$]	(0.026)	(0.023)	(0.024)	(0.024)	(0.021)	(0.020)	(0.020)
Observations	57,718	57,718	57,718	57,718	49,177	49,177	49,177
Panel B: Professor survey sample							
Fraction TAs Asian	−0.030	−0.072***	−0.041*	–	−0.159***	−0.063**	–
	(0.023)	(0.020)	(0.023)	–	(0.022)	(0.023)	–
Effect of Similar Race	0.065*	0.083***	0.077**	0.079**	0.120***	0.081***	0.118***
[$Asian_i$ * $AsianTA_{ikt}$]	(0.038)	(0.031)	(0.036)	(0.031)	(0.027)	(0.026)	(0.025)
Observations	33,399	33,399	33,399	33,399	28,683	28,683	28,683
Panel C: Single TA class							
Fraction TAs Asian	−0.051***	−0.070***	−0.052***	–	−0.077**	−0.037*	–
	(0.018)	(0.021)	(0.017)	–	(0.030)	(0.022)	–
Effect of Similar Race	0.090***	0.106***	0.096***	0.108***	0.109***	0.100***	0.113***
[$Asian_i$ * $AsianTA_{ikt}$]	(0.031)	(0.034)	(0.030)	(0.035)	(0.033)	(0.030)	(0.034)
Observations	17,500	17,500	17,500	17,500	16,841	16,841	16,841
Term FE	X		X			X	
Course FE	X		X			X	
Class FE				X			X
Student FE					X	X	X
Controls:							
Professor		X	X				
Student		X	X	X			
Student × Term		X	X	X			

Notes: "Effect of Similar Race" is Asian graduate TA composition interacted with an Asian student dummy. Standardized grade has a mean of zero and a standard deviation of one by class. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in the subject of the course, double major, class standing (Freshman/Sophomore/Junior/Senior), and professor gender and race. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.8
Tests for attrition — dummy for dropped class regressed on observables interacted w/TA race.

	Dropped class					
	(1)	(2)	(3)	(4)	(5)	(6)
Fraction TAs Asian interacted w/						
Student Asian	0.002	0.002	0.002	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Student female	−0.001	−0.001	−0.000	−0.001	−0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Admitted as transfer	−0.008*	−0.009*	−0.008	−0.016***	−0.018***	−0.020***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Student international	0.004	0.003	0.003	0.000	−0.001	−0.002
	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)
Student first generation	−0.002	−0.002	−0.002	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
High school GPA	−0.001	−0.001	−0.000	−0.004	−0.004	−0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Econ major	−0.001	−0.002	0.001	0.000	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Student double major	0.003	0.003	0.002	0.005	0.005	0.004
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Student age	0.002***	0.002**	0.002***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of Units up to class	−0.000	−0.000	−0.000	−0.000	−0.000*	−0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female professor	0.001	0.003		0.003	0.002	
	(0.003)	(0.003)		(0.003)	(0.002)	
Asian professor	0.001	0.002		0.001	0.002	
	(0.004)	(0.003)		(0.005)	(0.003)	
Observations	60,642	60,642	60,642	51,653	51,653	51,653
Term FE		X			X	
Course FE		X			X	
Class FE			X			X
Student FE				X	X	X

Notes: Each column presents results from a single OLS regression where the outcome is an indicator for whether the student dropped the class at any point during the term. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively. We find positive and statistically insignificant responses in class drop rates for students who are matched to TAs of similar race.

Table A.9
Alternative specifications using letter grades.

	Panel A: Coefficients	
	Ordered logit	Ordered probit
Asian students w/Asian TAs	0.067	0.034
	(0.042)	(0.024)
Non-Asian students w/non-Asian TAs	0.087**	0.050**
	(0.038)	(0.022)
Effect of Similar Race	0.153***	0.083***
[$Asian_i$*$AsianTA_{ikt}$]	(0.045)	(0.026)
N	57,718	57,718
log L	−131,532.85	−131,525.46
Pseudo-R^2	0.0326	0.0327

	Panel B: Marginal effects											
	F	D−	D	D+	C−	C	C+	B−	B	B+	A−	A
Ordered logit												
Asian students w/Asian TAs	−0.002	−0.001	−0.002	−0.002	−0.004	−0.004	−0.002	0.001	0.003	0.004	0.004	0.006
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)
Non-Asian students w/non-Asian TAs	−0.003**	−0.001**	−0.003**	−0.002**	−0.005**	−0.006**	−0.002**	0.001**	0.003**	0.005**	0.005**	0.008**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Effect of Similar Race	−0.005***	−0.002***	−0.005***	−0.003***	−0.008***	−0.010***	−0.004***	0.001***	0.006***	0.008***	0.009***	0.014***
[$Asian_i$*$AsianTA_{ikt}$]	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Ordered probit												
Asian students w/Asian TAs	−0.003	−0.001	−0.002	−0.001	−0.003	−0.003	−0.001	0.001	0.002	0.003	0.003	0.006
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Non-Asian students w/non-Asian TAs	−0.004**	−0.001**	−0.003**	−0.002**	−0.004**	−0.004**	−0.002**	0.001**	0.002**	0.004**	0.005**	0.010**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Effect of Similar Race	−0.006***	−0.002***	−0.005***	−0.003***	−0.007***	−0.007***	−0.003***	0.001***	0.004***	0.006***	0.008***	0.015***
[$Asian_i$*$AsianTA_{ikt}$]	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)

Notes: Panel A shows the estimated coefficients from ordered logit and ordered probit models. Panel B displays the marginal effects for each possible letter grade, evaluated at the controls' means. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in the subject of the course, double major, class standing (Freshman/Sophomore/Junior/Senior), and professor gender and race. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.10
Robustness of professor survey results.

	No multiple choice exams				Some/All multiple choice			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: Standardized grade								
Fraction TAs Asian	−0.132***	−0.139***	–	–	−0.002	−0.026	–	–
	(0.024)	(0.045)	–	–	(0.030)	(0.033)	–	–
Effect of Similar Race	0.196***	0.201***	0.199***	0.217***	0.046	0.035	0.046	0.040
[$Asian_i$ * $AsianTA_{ikt}$]	(0.041)	(0.065)	(0.042)	(0.070)	(0.055)	(0.044)	(0.056)	(0.048)
Observations	9185	8883	9185	8883	24,290	19,861	24,290	19,861
	Exams withheld from TAs				Exams shared with TAs			
Fraction TAs Asian	0.000	−0.105	–	–	−0.045	−0.039	–	–
	(0.032)	(0.095)	–	–	(0.035)	(0.045)	–	–
Effect of Similar Race	−0.000	0.075	−0.003	0.056	0.126**	0.155*	0.127**	0.172**
[$Asian_i$ * $AsianTA_{ikt}$]	(0.046)	(0.096)	(0.048)	(0.093)	(0.055)	(0.081)	(0.055)	(0.081)
Observations	9189	8296	9189	8296	19,119	15,503	19,119	15,503
Term FE	X	X			X	X		
Course FE	X	X			X	X		
Class FE			X	X			X	X
Student FE		X		X		X		X
Controls:								
Professor	X	X			X	X		
Student	X		X		X		X	
Student × Term	X	X	X	X	X	X	X	X

Notes: "Effect of Similar Race" is Asian graduate TA composition interacted with an Asian student dummy. Standardized grade has a mean of zero and a standard deviation of one by class. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in the subject of the course, double major, class standing (Freshman/Sophomore/Junior/Senior), and professor gender and race. All "Effect of Similar Race" specifications include course-by-race and term-by-race fixed effects. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.11
Additional professor survey results.

	Professor survey sample					
	All	(0)	(1)	(2)	(3)	(4)
Outcome: Standardized grade						
Effect of Similar Race	0.080**	0.066	−0.067	0.167	0.179	0.235***
[$Asian_i$ * $AsianTA_{ikt}$]	(0.036)	(0.039)	(0.057)	(0.097)	(0.128)	(0.046)
Multiple choice exams	–	Yes & No	Yes	Yes	No	No
Share exams with TAs	–	Yes & No	No	Yes	No	Yes
Class FE	X	X	X	X	X	X
Course × Race FE	X	X	X	X	X	X
Term × Race FE	X	X	X	X	X	X
Controls:						
Professor						
Student	X	X	X	X	X	X
Student × Term	X	X	X	X	X	X
Observations	33,997	27,837	7915	13,643	897	5382

Notes: Each cell reports the coefficient on the interaction between a student identifier for Asian and fraction of TAs Asian. The first column reports estimates for the subsample of classes where professors completed the survey. Column (0) considers the subsample of classes where professors answered both questions of interest. The remaining columns consider further survey subsamples. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in the subject of the course, double major, and class standing (Freshman/Sophomore/Junior/Senior). Standard errors are in parentheses, clustered by professor for Panels A and B, and clustered by TA for Panel C. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.12
Results for enrollment in another economics class and major in economics by subsample.

	Sample of interest					
	Full	Fr., So.	Juniors	Seniors +	Econ major	Other major
Enroll in another class						
Effect of Similar Race	0.008	0.021	0.001	0.004	0.003	0.020
[$Asian_i$ * $AsianTA_{ikt}$]	(0.008)	(0.017)	(0.013)	(0.016)	(0.007)	(0.016)
Observations	60,642	22,288	19,009	19,328	32,972	27,670
	2 + gen.	First gen.	Exams withheld	Exams shared	No MC	Some/All MC
Enroll in another class						
Effect of Similar Race	0.003	0.023	0.005	0.032*	0.035**	0.019
[$Asian_i$ * $AsianTA_{ikt}$]	(0.010)	(0.016)	(0.022)	(0.017)	(0.016)	(0.014)
Observations	37,232	23,410	9674	19,994	9765	25,323
	Full	Fr., So.	Juniors	Seniors +	Intro class	Adv. class
Major in Economics						
Effect of Similar Race	0.007	0.040*	0.004	−0.017	0.014	0.006
[$Asian_i$ * $AsianTA_{ikt}$]	(0.010)	(0.023)	(0.017)	(0.014)	(0.026)	(0.010)
Observations	60,642	22,288	19,009	19,328	22,366	38,276
	2 + gen.	First gen.	Exams withheld	Exams shared	No MC	Some/All MC
Major in Economics						
Effect of Similar Race	−0.002	0.028*	0.005	−0.005	−0.012	0.015
[$Asian_i$ * $AsianTA_{ikt}$]	(0.012)	(0.015)	(0.034)	(0.014)	(0.014)	(0.020)
Observations	37,232	23,410	9674	19,994	9765	25,323
Class FE	X	X	X	X	X	X
Controls:						
Professor						
Student	X	X	X	X	X	X
Student × Term	X	X	X	X	X	X

Notes: "Effect of Similar Race" is Asian graduate TA composition interacted with an Asian student dummy. "Enroll in another class" is an indicator for whether the student enrolled in another class in a future term. "Major in Economics" is an indicator for whether the student "finished" with an economics major. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in economics, double major, and class standing (Freshman/Sophomore/Junior/Senior). All specifications include course-by-race and term-by-race fixed effects. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.13
Class level analysis — primary data.

	Class average GPA		Class pass rate		Prof.-course z(GPA)	
	(1)	(2)	(3)	(4)	(5)	(6)
% Students Asian × % TAs Asian	0.190	0.173	0.088	0.071	0.060	0.055
	(0.177)	(0.172)	(0.056)	(0.054)	(0.128)	(0.127)
% TAs Asian	−0.115	−0.109	−0.046	−0.036	−0.053	−0.047
	(0.090)	(0.088)	(0.028)	(0.028)	(0.065)	(0.064)
% of Students Asian	−0.231*	−0.151	−0.029	0.003	−0.207**	−0.164
	(0.136)	(0.143)	(0.043)	(0.045)	(0.098)	(0.105)
% of Students female		0.030		0.071**		0.040
		(0.110)		(0.035)		(0.081)
Average age of students		0.013		0.019***		0.000
		(0.022)		(0.007)		(0.017)
% of Students international		−0.177		−0.169**		−0.148
		(0.223)		(0.071)		(0.164)
% of Students first generation		−0.042		0.006		0.028
		(0.132)		(0.042)		(0.097)
Average high school GPA of students		0.522***		0.119**		0.433***
		(0.168)		(0.053)		(0.124)
% of Students admitted as transfer		−0.049		−0.013		−0.003
		(0.170)		(0.054)		(0.126)

Average admission year		−0.000		0.000		−0.002
		(0.004)		(0.001)		(0.003)
% of Student Econ major		0.214*		0.065*		0.185**
		(0.113)		(0.036)		(0.083)
% of Students double major		0.021		−0.009		−0.170
		(0.165)		(0.052)		(0.121)
Average # of units up to class		−0.001		−0.001		−0.000
		(0.001)		(0.000)		(0.001)
Asian professor		0.104***		0.017**		0.013
		(0.024)		(0.007)		(0.017)
Female professor		0.060***		0.025***		0.012
		(0.020)		(0.006)		(0.015)
Course FE	X	X	X	X	X	X
Observations	614	614	614	614	614	614

Notes: This table contains six class-level regressions where the dependent variable is presented in the column header. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.14
Class level analysis — audit study.

	Dependent variable:		
	Fraction of attending students Asian	# of Asian students in attendance	# of White students in attendance
Fraction of TAs Asian	0.069	1.212	
	(0.048)	(16.386)	
Fraction of TAs White			12.752
			(13.702)
Observations	26	26	26

Notes: This table contains three class-level regressions where the dependent variable is presented in the column header. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.15
Tests for endogenous sorting — regression of TA race on observables.

	Full sample		Professor survey sample	
	(1)	(2)	(3)	(4)
Outcome: Fraction TAs Asian				
Fraction of students Asian	−0.026	–	0.355	–
	(0.266)	–	(0.402)	–
Fraction of student female	−0.351	−1.526	−0.866**	−1.228
	(0.286)	(1.132)	(0.437)	(1.883)
Fraction of students admitted as transfer	0.985*	−1.682	1.072	−3.998
	(0.530)	(1.938)	(0.756)	(3.324)
Average age of students	−0.076	0.131	−0.005	0.482
	(0.103)	(0.302)	(0.157)	(0.469)
Fraction of students international	0.122	2.938	−0.161	1.070
	(0.539)	(2.384)	(0.719)	(3.660)
Fraction of students first generation	−0.476	−0.663	−0.982**	−3.447
	(0.325)	(1.298)	(0.469)	(2.402)
Average high school GPA of students	−0.115	−1.365	0.323	−1.940
	(0.417)	(2.069)	(0.611)	(3.067)
Average admission year	0.097	0.028	0.721	0.718
	(0.351)	(0.358)	(0.492)	(0.517)
Fraction of student Econ major	−0.109	0.581	−0.161	2.914
	(0.276)	(0.912)	(0.415)	(1.769)
Fraction of students double major	−0.142	0.087	0.167	−1.041
	(0.399)	(1.530)	(0.593)	(2.913)
Average # of units up to class	0.009	−0.006	0.020*	−0.009
	(0.008)	(0.014)	(0.011)	(0.023)
Female professor	−0.061	−0.149	−0.083	−0.161
	(0.048)	(0.213)	(0.071)	(0.368)

Asian professor	0.104*	0.013	0.151	−0.012
	(0.056)	(0.290)	(0.099)	(0.673)
Fraction Asian × Fraction female		2.229		0.575
		(2.168)		(3.545)
Fraction Asian × Fraction admit as transfer		5.503		10.345
		(3.772)		(6.406)
Fraction Asian × Average age		−0.449		−0.932
		(0.558)		(0.867)
Fraction Asian × Fraction international		−4.957		−2.728
		(4.170)		(6.543)
Fraction Asian × Fraction first generation		0.412		4.849
		(2.506)		(4.539)
Fraction Asian × Average high school GPA		2.450		4.627
		(4.137)		(5.962)
Fraction Asian × Average admission year		−0.022		−0.184
		(0.104)		(0.177)
Fraction Asian × Fraction same major as class		−1.401		−5.928*
		(1.803)		(3.355)
Fraction Asian × Fraction double major		−0.387		2.387
		(2.968)		(5.335)
Fraction Asian × Average # of units up to class		0.028		0.056
		(0.023)		(0.036)
Fraction Asian × Female professor		0.193		0.167
		(0.425)		(0.713)
Fraction Asian × Asian professor		0.195		0.353
		(0.585)		(1.372)
Course & Term FE	Yes	Yes	Yes	Yes
P-value: Joint significance	0.261	0.709	0.251	0.509
R-squared	0.183	0.190	0.296	0.319
Observations	614	614	334	334

Notes: Each column presents results for a regression where the dependent variable is the fraction of the class's TAs that were Asian. Coefficients for term and course FE are not shown. *P*-value for joint significance of all individual covariates, conditional on term and course FE, included. The first column includes all baseline characteristics for the class. The second column includes interactions of the fraction of students who were Asian in the class with the baseline characteristics for the class. The next two columns repeat this analyses but for the sample of classes taught by professors who participated in our survey. Standard errors are in parentheses. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

Table A.16
Main results — drop 16 classes which had same course-term-instructor.

	Standardized grade				Passed class			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full sample								
Effect of Similar Race	0.085***	0.081***	0.084***	0.070***	0.018**	0.032***	0.020**	0.018**
	(0.025)	(0.021)	(0.024)	(0.026)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	55,355	47,338	55,355	55,355	56,725	48,470	56,725	56,725
Panel B: Professor survey sample								
Effect of Similar Race	0.085**	0.086**	0.085**	0.077**	0.017	0.028**	0.016	0.015
	(0.035)	(0.035)	(0.034)	(0.035)	(0.011)	(0.012)	(0.011)	(0.011)
Observations	32,211	27,985	32,211	32,211	32,948	28,603	32,948	32,948
Term FE			X	X			X	X
Course FE			X	X			X	X
Class FE	X	X			X	X		
Student FE		X				X		
Controls:								
Professor			X				X	
Student	X		X		X		X	
Student × Term	X	X	X		X	X	X	

Notes: "Effect of Similar Race" is Asian graduate TA composition interacted with an Asian student dummy. Standardized grade has a mean of zero and a standard deviation of one by class. Controls include age when class began, high school GPA, and admission year, as well as indicators for student gender, international vs. domestic, whether parents attended college, admittance (transfer vs. freshman), whether the student is majoring in economics, double major, class standing (Freshman/Sophomore/Junior/Senior), and professor gender and race. All specifications include course-by-race and term-by-race fixed effects. Standard errors are in parentheses, clustered by professor. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 % levels, respectively.

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