Affirmative Action, Faculty Productivity and Caste Interactions: Evidence from Engineering Colleges in India

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Abstract

Affirmative action programs are often criticized because of concerns that they result in lower worker productivity and efficiency losses. We study the relative productivity of workers benefiting from an aggressive affirmative action policy in a setting where hiring constraints are especially likely to bind. In India, colleges are required to reserve approximately 50 percent of faculty hires for individuals from lower caste and social class groups ("reservation category"). We collect and analyze data from a nationally representative sample of 50 engineering and technology colleges in India, some of which randomly assign students to classrooms. We find that reservation category faculty have lower levels of education, lower professorial ranks and fewer years of experience in academia than general category faculty who are not hired through reservations. Yet, even with lower qualifications, we find no evidence that reservation category faculty provide lower quality instruction across a wide range of measures that include course grades, follow-on course grades, standardized test scores, dropout, attendance, graduate school plans, and graduation. In fact, we find that, at least for immediate effects on course grades, students taught by reservation category faculty perform slightly better than students taught by general category faculty. Colleges in India also reserve approximately 50 percent of student admissions for lower caste and social class groups. Examining student performance we find that reservation category students obtain lower grades than general category students even after controlling for differences in parental education, baseline test scores, and entrance exam scores. Reservation category students also score lower on math, physics, electrical engineering and computer science tests but do not differ in dropout and expected graduation rates. Finally, we explore student-faculty interactions and do not find evidence of positive "teacher-like-me" effects of reservation category faculty on the relative course performance and longer-term outcomes of reservation category students. Even in the face of potential discrimination and resentment against quotas, general category students perform slightly better in classrooms taught by reservation category faculty than general category faculty. The findings have implications for the heated debates over affirmative action programs found in many countries around the world and in India which is now the largest country in the world.

Keywords: Affirmative action, caste, reservation, student-faculty diversity gap, worker productivity, instructional quality, inequality, STEM

JEL Codes: J78, J15, I24, I23

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1 Introduction

Organizations around the world are attempting to increase the diversity of their workforces through affirmative action programs (Fryer & Loury, 2013; Sowell, 2008). Recently, for example, large tech companies have pledged support for affirmative action programs in college admissions to help them diversify their highly educated workforce (for which they have been criticized).[1] The primary goals of affirmative action programs are to counter the effects of past discrimination and reduce economic, social and political inequality. Government departments, health care and educational institutions, and law enforcement agencies have the added goal of closer representing their workforces to the populations they serve because of the potential for positive spillovers, especially for disadvantaged groups. The potential benefits of affirmative action programs are considered so important to counteract historically ingrained discrimination that they are even included in national and state constitutions.[2]

A commonly made criticism of affirmative action programs is that workers hired through such programs have lower qualifications and are accordingly less productive. Lower qualifications among workers targeted by affirmative action, however, do not necessarily imply lower worker productivity. For example, if workers targeted by affirmative action face discrimination in the private sector but not the public sector, then higher ability workers may sort into public sector jobs while lower ability workers may sort into private sector jobs. In this type of situation, the average productivity of targeted workers in the public sector may actually be higher than their non-targeted colleagues in the public sector. Additionally, in firms that would otherwise discriminate but instead adopt affirmative action policies, workers hired through the policies may be more qualified and productive because they no longer face discrimination (Holzer & Neumark, 1999). In fact, a sparse literature finds "clear evidence of weaker credentials but more limited evidence of weaker labor market performance among the beneficiaries of affirmative action" (pg. 474, Holzer & Neumark, 2006).

Colleges, in general, are in the unique and interesting position of increasing diversity of not only

[1] In the recent Supreme Court case against Harvard University and the University of North Carolina over affirmative action in college admissions, more than 70 major corporations from a broad range of sectors signed a brief in support of continuing affirmative action programs in admissions (*Student for Fair Admissions, Inc. v. President and Fellows of Harvard College*, 2022). The Supreme Court, however, ruled on June 29, 2023 that colleges can no longer take race into consideration when granting admission offers.

[2] In India's Constitution, for example, approximately half of the positions in political bodies, various forms of employment and promotion, as well as education admissions, are reserved for lower caste and lower social class groups (Article 15, CoI, 1948).

their faculty workforce, but also their student (consumer) base. In this context, an additional commonly made argument for increasing faculty diversity through affirmative action programs is to improve the performance of college students from historically disadvantaged, underrepresented, or discriminated against groups (CCCCO, 2020; CPRHE, 2018; UCOP, 2018). These faculty might serve as role models, decrease the likelihood of "stereotype threat" and discrimination against minority students, increase exposure to instructors with similar cultures and languages, and contribute to a sense of belonging at the university and major (Bettinger & Long, 2005; Birdsall, Gershenson, & Zuniga, 2020; Carrell, Page, & West, 2010; Dee, 2005; Fairlie, Hoffmann, & Oreopoulos, 2014).

In this paper, we examine the relative productivity of workers benefiting from an aggressive affirmative action policy in a setting where constraints on hiring a diverse qualified workforce are likely to bind. Specifically, we examine the reservation policy in colleges in India which set strict quotas on hiring half of faculty and admitting half of students from lower caste and social class groups. We first examine whether college faculty hired through quotas ("reservation category faculty") have lower observable credentials or qualifications. We then test whether reservation category faculty are less, or more, productive than general category faculty. We also identify "true" overall differences in performance—conditional on faculty quality as well as the composition of classrooms—between reservation category students who are admitted through quotas and general category students who are not admitted through quotas.[3] Finally, we test whether reservation category faculty particularly improve the performance of reservation category students (i.e. "teacher-like-me" effects), and the related question of whether general category students perform worse (in absolute terms) in classes taught by reservation category faculty because of possible discrimination and resentment towards quotas.

We explore these questions using a novel, large, and nationally representative dataset that we collected on faculty and undergraduate students at 50 engineering and technology colleges in India. Most of the analyses focus on a subset of these colleges that randomly assign students to classrooms. We collect and analyze a comprehensive set of measures of faculty productivity including effects on immediate course grades, follow-on course grades, test scores in math, physics, electrical engineering (EE) and computer science (CS), dropouts, expected graduation with a degree and additional

[3] Students belonging to disadvantaged caste groups have historically had lower levels of educational attainment (Frisancho & Krishna, 2016; Khanna, 2020), but caste disparities in levels and gains in the same courses and taught by the same faculty have not been estimated in the previous literature.

longer-term student outcomes, as well as faculty research productivity such as publications, grants received, and administrative activities.

Estimating the effects of being taught by reservation category faculty on student performance, however, is usually fraught with issues of potential selection bias. First, general category students who have more animosity or believe that they cannot learn as well from reservation category faculty might avoid those classes. Second, reservation category students may sort into classes taught by reservation category faculty. Third, administrators might assign reservation category faculty to different, perhaps easier or less important courses, than general category faculty. Both sorting by students and faculty, and differential sorting into courses taught by reservation category faculty potentially contaminate comparisons between reservation and general category faculty teaching.

To address these threats to identification, we analyze data from the engineering colleges that randomly assign students to faculty-taught classroom sections within courses. Random assignment of students to classes does not typically occur in higher education with only a few exceptions.[4] Another important feature in these colleges is that student marks are given at the course level and through end-of-semester standardized exams administered and graded by a higher-level university system that includes many colleges (referred to as the "university" in the setting of these colleges) instead of assessments or evaluations by individual faculty. This grading policy rules out the possibility, for example, that reservation category faculty favorably treat reservation category students through higher course marks. Also, similar to core courses in the U.S. Air Force Academy studied in Carrell et al. (2010) and Carrell and West (2010), course content is standardized, and professors use a similar syllabus to that prescribed by the All India Council for Technical Education (AICTE, 2018). Random assignment in this setting also allows us to directly estimate the effects of reservation category faculty on general category students, removing the reliance on difference-in-difference estimates that use the base or majority group as a comparison group (e.g. Egalite, Kisida, & Winters, 2015; Fairlie, Hoffmann, & Oreopoulos, 2014; Gershenson, Holt, & Papageorge, 2016).[5] We are interested in not only the relative effect of reservation category faculty on reservation cate-

[4] Random assignment takes place at the U.S. Air Force Academy that provides undergraduate education for officers in the U.S. Air Force (Carrell, Page, & West, 2010). A relatively new literature uses random assignment of registration priorities and discontinuities in wait lists to provide exogenous variation in the level of course choice among college students (Kurlaender, Jackson, Howell, & Grodsky, 2014; Robles, Gross, & Fairlie, 2021).

[5] We further build on the identification provided by random assignment by including student, faculty, and classroom fixed effects as used in estimating difference-in-difference regressions for "teacher-like-me" effects.

gory students but also the absolute and separate effects of reservation category faculty on general category students because of potential animosity and discrimination.

We find that reservation category faculty at engineering colleges in India have lower professorial ranks, fewer years of experience, and lower educational credentials than general category faculty. However, these lower observable qualifications do not translate into lower quality teaching. We find that reservation category faculty actually teach slightly better than general category faculty as measured by course grades; students taught by reservation category faculty have a higher percentile rank for a given course, with the magnitude of difference varying between 1.3 to 1.5 percentile points. The results are statistically significant, and robust to the inclusion of various sets of faculty characteristics as controls, student fixed effects, and course fixed effects. Reservation category faculty do not put more time into teaching, measured along a range of dimensions, and thus do not provide more, but lower-quality, instruction to students. Consistent with the findings for immediate effects on course grades, we do not find evidence of negative reservation category faculty effects on longer-term outcomes such as follow-on course grades, test scores (math, physics, EE and CS), course attendance, dropouts, expected graduation with a degree, and graduate school plans. We also do not find that research productivity and administrative service are lower among reservation category faculty than general category faculty.[6] Taken together, the findings are consistent with discrimination in the private labor market pushing high-ability lower caste and social class workers into academic jobs which are covered by affirmative action.

Focusing on the relative performance of reservation category students, we find that they obtain lower grades and score lower on endline tests than general category students. The differential of 4-6 percentiles in course grades remains even after controlling for baseline test score differences. Reservation category students admitted based on lower entrance exam cutoffs might be less prepared to do well in engineering courses. However, we do not find differences in dropouts, expected graduation rates, and plans for graduate school.

We also do not find evidence of "teacher-like-me" effects. There is no statistically significant difference between the performance of reservation category students taught by reservation category

[6]Engineering colleges in India have not traditionally placed an emphasis on research productivity among their faculty (similar to the typical or representative college in the U.S.). The primary basis for promotions and evaluations is experience and degree qualifications (AICTE 2010).

faculty, and reservation category students taught by general category faculty. These results hold for both course grades and longer-term outcomes such as follow-on course grades, test scores, course attendance, dropout, and expected graduation with degree. We also find that even in the face of resentment and possible discrimination, general category students obtain slightly better grades (in absolute terms) in classrooms taught by reservation category faculty than general category faculty. These findings have implications for the heated debates over affirmative action programs in many countries around the world.

Engineering and technology colleges in India provide an important testing ground for understanding the relative productivity of workers hired through affirmative action. India is now the largest country in the world, and has the most aggressive affirmation action program in higher education in the world, eliminating the student-faculty diversity gap and even the typically wider population-faculty diversity gap.[7] Being qualified to teach at the college level is a rare skill in India, where less than 6 percent of the prime-age population has at least a Master's degree (the minimum qualification required to teach at engineering and technology colleges) and less than 2 percent of the reservation category population has a Master's degree (see Table A1). There are widely stated concerns about heterogeneity in faculty quality, as well as shortages of qualified faculty to teach in engineering and technology colleges (The Hindu, 2021; The Indian Express, 2017, 2018, 2021).[8] On the other hand, there is considerable discrimination in the private labor market against workers of lower caste and social class (see, for example, Wired, 2022). The Indian IT industry, in particular, has been criticized for not expanding their pool of workers to include lower caste and social class groups (Madheswaran & Attewell, 2007; Shukla, 2022; Upadhya, 2007).[9] Moreover, the scale of the reservation program is immense: engineering and technology colleges employ roughly a quarter of a million faculty and roughly 4.5 million students are enrolled in these colleges (AICTE, 2023; Ministry of Education, GoI, 2020). Engineering colleges in India account for nearly 25 percent of

[7] Approximately half of faculty and student positions are reserved for the Scheduled Castes (SCs), Scheduled Tribes (STs), and Other Backward Classes (OBCs) based on their representation in the population. The Scheduled Castes (SCs) are based on the historically based caste system, the Scheduled Tribes (STs) are based on indigenous tribal membership, and the Other Backward Classes (OBCs) are based on social and educational disadvantage. In contrast, for example, in the largest higher-education system in the United States, the California Community College system, 51 percent of enrolled students are from underrepresented groups, but only 21 percent of tenured faculty are from the same groups (Ed Source, 2020).

[8] Reservation policies in India have faced substantial criticism and resistance (MoHRD, GoI, 2020; The New York Times, 2015; The New York Times, 2022; Weisskopf, 2004).

[9] Lower-caste students are found to have lower returns to education (Bertrand, Hanna, & Mullainathan, 2010; Madheswaran & Attewell, 2007; Mitra, 2019; Shukla, 2022).

all engineering degrees awarded each year globally (NSF, 2018).[10] Finally, focusing on engineering and technology colleges is important because degrees result in high-paying jobs and contribute substantially to upward economic and social mobility for lower-caste and lower social class groups.

Our paper contributes to two major strands of the literature. First, we contribute to the literature on affirmative action policies from the vantage point of worker productivity and efficiency loss. Previous studies find that workers hired through affirmative action policies have lower qualifications but the evidence on worker productivity is more limited (Holzer & Neumark, 2006).[11] We provide new evidence on affirmative action workers having similar (or even slightly higher productivity as measured by course grades) along a key dimension of their jobs. Our analysis provides novel findings on affirmative action and faculty positions in general, and provides some of the first evidence focusing on reservations and worker productivity in India. The closest evidence on reservations and worker productivity examines the relationship between TFP and affirmative action worker shares in the Indian railways system using aggregate data from eight regional railway zones from 1980 through 2002 and finds no evidence of reduced efficiency (A. Deshpande & Weisskopf, 2014). The literature is surprisingly thin. Research in India has primarily focused instead on reservation policies and political positions (Bhavnani & Lee, 2021), and on reservation policies for student admissions and outcomes such as enrollment (Bagde, Epple, & Taylor, 2016; Bertrand, Hanna, & Mullainathan, 2010; Cassan, 2019; Weisskopf, 2004), and future labor market outcomes (Bertrand, Hanna, & Mullainathan, 2010; Shukla, 2022). Our paper is the first to take advantage of random assignment of students to classrooms to alleviate concerns over selection bias in estimating faculty productivity on immediate and long-term outcomes.

Second, we contribute to the growing literature on the interaction effects of disadvantaged teachers on disadvantaged students across all levels of education (i.e. "teacher-like-me" effects). Several previous studies focus on racial interactions and find evidence of strong positive student-teacher interactions by race at the primary and secondary school levels (Dee, 2004, 2005; Egalite, Kisida, & Winters, 2015; Ehrenberg, Goldhaber, & Brewer, 1995; Gershenson, Hart, Hyman, Lindsay, & Papageorge, 2022; Gershenson, Holt, & Papageorge, 2016; Lindsay & Hart, 2017; Tran & Gershenson,

[10] Scientists and engineers from India represent more than 20 percent of all foreign-born science and engineering degree holders working in the United States (NSF, 2018).

[11] Recent studies have focused on whether temporary affirmative action programs have long-term effects on employment of targeted groups. See Kurtulus (2016); A. R. Miller and Segal (2012); C. Miller (2017), for example.

2021) and college level (Birdsall, Gershenson, & Zuniga, 2020; Fairlie, Hoffmann, & Oreopoulos, 2014; Oliver, Fairlie, Millhauser, & Roland, 2021; Price, 2010).[12] With the exception of the studies using the 1985-1989 Tennessee STAR experiment, however, these studies of racial interactions do not leverage random assignment of students to teachers, and thus rely on estimating relative effects instead of absolute effects.. Furthermore, we address potential concerns over differential effects between immediate and longer-term educational outcomes finding similar results (Gershenson, Hart, Hyman, Lindsay, & Papageorge, 2022). Student-teacher interactions based on caste in India have been studied much less, and the evidence is limited to K-12 levels. These studies find both negative and positive interactions (Hanna & Linden, 2012; Karachiwalla, 2019; Rawal & Kingdon, 2010). Our study is the first to explore faculty-student interactions based on caste and affirmative action groups, in the context of post-secondary education in India. Random assignment to classrooms also allows us to study for the first time the broad question of how students from advantaged groups perform when taught by teachers from less-advantaged groups in the face of potential discrimination and resentment towards hiring quotas.[13]

The remainder of the paper is organized as follows. In Section 2, we discuss the caste system and reservation policies in India, and provide new descriptive results on caste inequality in educational and economic outcomes from National Sample Survey (NSS) microdata. Section 3 describes the data and classroom assignment procedure. Section 4 describes the econometric methods for estimating instructional quality and teacher-like-me effects. Section 5 presents the main results for faculty qualifications and productivity (educational, research and administrative). Section 6 explores differences in student performance between reservation category and general category students. Section 7 explores teacher-like-me effects. Finally, Section 8 concludes.

2 Caste System and Reservation Policy Setting

The Indian caste system is a hierarchical social stratification framework, which has been a part of Indian society since as far back as 1500 BC. The caste system comprises four hierarchical classes, or *varnas*, with each class consisting of potentially thousands of castes, or *jatis*, with their own

[12] See, for example, (Carrell, Page, & West, 2010; Dee, 2005; Hoffmann & Oreopoulos, 2009) for studies of gender interactions.

[13] General category students in India express concerns about the quality of instruction and non-meritorious hiring of lower-caste faculty, and mention not putting as much effort into courses taught by lower-caste faculty (S. Deshpande, 2006; Jodhka & Newman, 2007).

hierarchies within each class. In addition, a large set of social groups, referred to as *Dalits*, were historically excluded from the four classes, and were considered "untouchable." In addition to a signal of social hierarchy, caste also has an economic function as an indicator of occupational groups, with each caste historically mapped to an occupational guild. Endogamy, or marriage within caste groups (commonplace since at least the last 1900 years (Moorjani et al., 2013)), has led to a degree of persistence in the caste-occupation mapping (Munshi, 2019).

After independence from British colonial rule in 1947, the Indian government established an affirmative action system, called "reservation," that sought to increase the representation of historically disadvantaged castes in public education, central and state government positions, and local and national politics. The groups for whom these reservations were put in place were the formerly "untouchable" castes (i.e, Scheduled Castes), marginalized indigenous groups (Scheduled Tribes), and, following the Mandal commission report in 1990, historically disadvantaged groups within the four *varnas* (Other Backward Classes).

The intersection of caste with economic outcomes has been of profound interest to researchers across multiple disciplines in the social sciences. Previous studies have looked at caste-based heterogeneity of outcomes in labor markets (Banerjee, Bertrand, Datta, & Mullainathan, 2009; Dayanandan, Donker, & Nofsinger, 2019; A. Deshpande & Newman, 2007; Shukla, 2022; Thorat & Attewell, 2007), internal firm dynamics (Aswani, 2020; Bhagavatula, Bhalla, Goel, & Vissa, 2017, 2022), social network effects based on caste (Fisman, Paravisini, & Vig, 2017; Munshi, 2011, 2019; Munshi & Rosenzweig, 2006, 2016), and education (Hanna & Linden, 2012; Hnatkovska, Lahiri, & Paul, 2012, 2013; Rawal & Kingdon, 2010). Caste differences in education are an important area of concern; historically disadvantaged castes have a lower rate of return to higher education relative to advantaged castes (Madheswaran & Attewell, 2007; Mitra, 2019), and improvements in educational outcomes for disadvantaged castes are a major source of convergence of wages and consumption levels between advantaged and disadvantaged castes (Hnatkovska, Lahiri, & Paul, 2012, 2013).

Published reports or papers showing caste differences in educational and economic outcomes are limited. To fill this void, we analyzed microdata from the nationally representative Employment and Unemployment Survey conducted by India's National Sample Survey (NSS) Organization in 2011. The NSS microdata provide detailed information on reservation groups, educational attainment, labor market outcomes, and income. Appendix Table A1 reports differences between general category and reservation category population. Starting with educational attainment, we find large differences between the general category and reservation group population, with the general category on average having spent close to 3 additional years in school, and high school and college graduation rates for the general category being 17.5 percentage points and 12.9 percentage points higher respectively.

Employment in regular jobs is much lower among groups qualifying for reservation policies, with the general category population having a 14% higher regular employment rate than the reservation category population. Weekly wages, conditional on regular employment, are also much lower for the reservation category population, both for the subset of the surveyed population who are college graduates and younger college graduates between ages 25 to 45 years. Monthly per capita consumption expenditure for reservation category households is also significantly lower than general category households, both in rural and urban settings.

3 Data and Classroom Assignment

3.1 Nationally Representative Sample

To study faculty productivity and faculty-student interactions we collected student, faculty and administrative data from a nationally representative sample of 50 engineering and technology colleges in India. We drew nationally representative samples of faculty and students from broadly defined computer science (CS) and electrical engineering (EE) majors, the two largest majors in engineering and technology colleges. The sample captures the typical or representative experience of college students and faculty and does not focus on only more selective research or so-called "elite" colleges in India.

The sampling procedure consisted of three main steps.[14] In the first step, we identified a broad set of CS and EE majors or departments. CS and EE related departments were selected as these departments draw the highest enrollment, accounting for approximately half of the engineering and

[14]The first phase of data collection took place from October-December 2017. The second phase of data collection took place from January-March 2019.

technology college enrollment in India.[15] Furthermore, these departments comprise roughly one out of every four undergraduate (bachelor's degree) majors in STEM in India. The CS departments included Computer Engineering, Computer Science Engineering, Information Science and Engineering, and Information Technology departments. The EE departments included Electrical Engineering, Electronics and Communication Engineering, Electronics and Electrical Engineering, Electronics and Instrumentation Engineering, and Electronics and Telecommunications Engineering departments. In the second step, we randomly selected colleges that had these CS and EE programs. To do so, we used administrative data on (the population frame of) all colleges with CS and EE programs in the country. We also randomly selected colleges from elite and non-elite college strata. Specifically, we used simple random sampling to select 8 elite colleges and probability proportional to size sampling to select 42 non-elite colleges.[16] The national sample of colleges thus represent the range of elite and non-elite institutions in India. In the third step, we sampled students within CS and EE programs in the selected universities. We first randomly sampled 1 CS department and 1 EE department from each college. In each randomly sampled department, we sampled all first-year students. For all students, we create sample weights that reflect the inverse probability of being sampled at the college, department, and student levels.

Our student survey involved collecting data on the coursework completed by students at the time of taking the survey as well as the faculty who taught these courses. We then mapped this information to the data collected from surveying faculty, where we also obtained information on a faculty's "reservation category status," i.e, whether they belonged to the general category or one of the three reservation category groups. In addition to the student and faculty surveys at each college, we also surveyed department heads. We collected data for 20,239 students, and data for the 2,710 faculty that taught their courses.

To collect these data, we had the full support of the government (in particular, the Ministry of Human Resource Development and the AICTE)—and hence college and department administrators—to conduct the study. We also spent considerable time training a large team of enumerators that proctored the survey and assessments in person at each college. They also remained for 2-3

[15] Loyalka et al. (2022) calculate these estimates using administrative data with complete national coverage in India.

[16] Elite institutions were defined as the India Institutes of Technology (IITs), the Indian Institutes of Information Technology (IIITs), the National Institutes of Technology (NITs), and other institutions that ranked in the top 100 of the National Institutional Ranking Framework (NIRF) rankings developed by the Ministry of Human Resource Development, Government of India.

days at each college to make sure that students were able to participate even if they were unavailable on a particular day. As such, response rates were extremely high. Among enrolled students at the time of the baseline, approximately 95 percent participated in the baseline survey and assessments. Similarly, among enrolled students at the time of the endline or follow-up survey, approximately 95 percent participated in the endline survey and assessments.

3.2 Faculty Characteristics and Qualifications

We report new findings on faculty characteristics and qualifications, from our nationally representative sample of 50 engineering and technology colleges. Average faculty characteristics and qualifications are reported in Table 3.1. Column 1 reports means, and Column 2 reports standard deviations. Granted that engineering and technology colleges follow reservation policies, 50 percent of faculty in our nationally representative sample belong to the reservation category. Most engineering and technology faculty in India are at the assistant professor rank (77 percent) whereas a smaller share are associate professors (13 percent) and full professors (6 percent). On average, faculty at engineering and technology colleges have 9.49 years of work experience in higher education. In terms of educational background, master's degrees are the minimum educational requirement for faculty and are the most common education level (61 percent). We did not find any faculty with lower levels of education. Fewer faculty have a completed PhD (17 percent) or a PhD in progress (19 percent). Twenty-five percent of faculty received their degree from one of the elite engineering and technology colleges in India. Thirty-four percent of faculty are female.

Table 3.1: Faculty and Student Characteristics in Engineering and Technology Colleges in India

Attribute		
	Faculty	
	Mean	SD
Reservation Category	0.50	0.50
Assistant professor	0.77	0.42
Associate professor	0.13	0.34
Professor	0.06	0.23
Experience (years)	9.49	6.86
Highest degree Master's	0.61	0.49
Highest degree PhD in progress	0.19	0.39
Highest degree PhD	0.17	0.38
Degree from elite college	0.25	0.43
Female	0.42	0.49
N	2710	2710
	Students	
	Mean	SD
Reservation Category	0.56	0.50
Female	0.41	0.49
Age (years)	18.95	1.49
Father attended college	0.48	0.50
Mother attended college	0.35	0.48
N	20239	20239
Number of colleges	50	
Number of departments	100	

Note: Estimates use department-level sampling weights defined across the full national sample of surveyed colleges (50 colleges).

3.3 Student Characteristics

Table 3.1 also reports student characteristics from our nationally representative sample of 50 colleges. Approximately 56 percent of students belong to the reservation category. The mean student age is 18.95, and 41 percent of engineering students are female. Engineering students in India come from well-educated families. Roughly one half of the students have a college-educated father, and 35 percent have a college-educated mother. These levels of educational attainment are much higher than the general population as reported in Appendix Table A1, wherein we find that less than 20 percent of even the general category population graduated from college.

3.4 Colleges and Departments with Random Assignment to Classrooms

Using surveys conducted with department heads, we found that students in a subset of departments were randomly assigned to "classrooms" or sections for all courses taken during the first two years of college. These departments indicated they used a formal, computerized procedure for the random assignment. We also obtained granular course-level grade information from these departments (in 12 colleges) for all courses taken by students during the first two years.

Students enroll in courses each term in which there are typically multiple "classrooms." Classrooms are defined as separate course sections taught by faculty during the same term to maintain small classroom sizes. For example, Electrical Engineering 101, Spring 2019 at College A is a course that might have three separate classrooms: Section A which is taught by Faculty X, Section B is taught by Faculty Y, and Section C is taught by Faculty Z. Each classroom would have roughly one third the total course enrolment for that semester. The number of classrooms for a course ranges from 1 to 15, with a median of 3 classrooms per course. Courses are distinctly defined for each college and department.

Students within a given department generally enroll in the same set of courses prescribed during the first two years of college (AICTE, 2018). Within each of these prescribed courses the random allocation of students to course sections or classrooms within department ensures that students do not self-select into classrooms with varying compositions (in terms of proportions of reservation category faculty/peers or any correlated characteristics) of faculty and classmates. Consequently, for this sample of colleges, we can estimate the causal effects of being assigned a reservation category faculty (or other faculty characteristics) on student course grades.

3.5 Course Grades

Course grades in our sampled colleges are determined by assessing student performance on traditionally administered exams. Important to this study, course grades are assigned based on end of semester exams that are conducted and graded by a higher-level entity, which in the context of colleges in India is called the "university" and is the equivalent of a university system. Thus, faculty assigned to classrooms within the same course do not have direct control over assessing student performance. Instead, a higher-level "university" agency grades the final exams for the course for which a majority of the final grade is based.[17]

Grades are not standardized across the colleges. Some colleges provide letter grades whereas some colleges provide grades on a scale of 1-100. We standardize across courses and colleges by creating a ranking of all students within a course. This creates variation in course rankings across classrooms taught by different faculty. Note that course rankings by definition have mean 50 and standard deviation 28.9, because rankings follow a uniform distribution, which has a mean of $\frac{(a+b)}{2}$ and a variance of $\frac{(b-a)^2}{12}$, with $a = 0$ and $b = 100$. Most of our analyses use college-department-course ("course") fixed effects, alleviating concerns about comparability.

3.6 Sample with Random Assignment

For the sample of 12 colleges (20 departments) where students are randomly allocated to classrooms within courses and for which we obtained course-level grades, we have 2,268 students who are enrolled in 1,277 classrooms, within 415 distinct courses, and taught by 501 different faculty.[18] Each classroom is taught by only one faculty. Students assigned the same classrooms are taught by the same faculty for the entire semester. The average classroom size is 30 students and the average course size is 92 students. Our main analysis sample follows one cohort of students over their first two years of coursework.

Appendix Table B1 reports faculty qualifications and student characteristics for our sample of 12 colleges that randomly assign students to classrooms. Columns 3 and 4 reports means and standard deviations. We find that 40 percent of faculty belong to the reservation category in our sample with random assignment. Most professors are at the assistant professor rank (72%), and fewer are at the associate (18%) and full (8%) professor ranks. Faculty have 9.96 average years of experience in higher education. Most faculty have a master's degree (51%) and fewer have a PhD in progress (15%) and completed PhD (32%). Roughly one-third of faculty earned their degree from an elite college and one-third are female. These qualifications are reasonably similar to those of faculty in the national sample. The main differences are that the sample with random assignment has a lower share of reservation category faculty and female faculty, but a higher share of faculty with a completed PhD, and faculty with degrees from elite colleges. The general patterns are similar

[17] Our sample includes a few departments, where a proportion of the grading structure can be under the instructors' control. But, this proportion is small and never exceeds 30 percent in our sampled colleges.

[18] Attrition from baseline to endline for this sample was less than 4 percent.

though.

The bottom panel of Appendix Table B1 reports student characteristics for our sample with random assignment. We find that 54 percent of students belong to the reservation category, 44 percent are female, and the average age is 17.72 years. We find that 50 percent have a college-educated father, and 35 percent have a college-educated mother. The student characteristics for the 12-college sample are similar to those for the national sample.

In addition to course grades, we collected information on several longer-term outcomes. These outcomes are measured at the end of the first two years. First, we have information on scores from standardized and proctored math and physics tests that we administered. It is extremely rare to have test scores in analyses of university education. We also collected information on class attendance and dropout. To further capture effects on advanced and experiential learning in engineering, we also asked all of the students about whether they planned to eventually go to graduate school and whether students report working on research with professors.

3.7 Additional Cohort of Students

We also collected data on a few longer-term educational outcomes measured at the end of the four-year program for a second cohort of students. For this cohort of students, we collected less information on educational outcomes and do not have course grades. We combined survey information with administrative information to capture major-specific test scores (computer science and electrical engineering), graduate school plans, and expected graduation with a degree for this second cohort of students, all of which are measured at the end of the four-year programs. We also have data on faculty characteristics including reservation category status for all courses taken in the first two years for each student for our sample of colleges with random assignment. This cohort includes 2289 students taught by 650 different faculty. We use this second cohort of students to study additional long-term outcomes of students by reservation category of students and faculty.

4 Econometric Methods

4.1 Instructional Quality Regression Model

To test for differences in worker productivity as measured by instructional quality between general category and reservation category faculty, we estimate several regressions for educational outcomes. We present equations in which the student course grade is the dependent variable which serves as a starting point for regressions for longer-term educational outcomes. Since grading is done at the course level and not classroom level, and by an independent group and not each instructor, course grades are a good indicator for immediate teaching performance. The base regression for student grades is the following:

$$Y_{ikcf} = \alpha + \beta_1 RT_f + \gamma_2 T_f + \lambda_k + \lambda_i + \epsilon_{ikcf} \tag{4.1}$$

where Y_{ikcf} is the outcome for student i in course k, taught in classroom c by faculty f, RT_f is a dummy variable indicating the reservation category status of faculty f (equals 1 if the faculty belongs to the reservation category, and 0 if they belong to the general category), T_f is a vector of teacher characteristics for faculty f, λ_k are course fixed effects, λ_i are student fixed effects, and ϵ_{ikcf} is the error term.[19] Classrooms are taught by only one faculty and are within courses. Since students take multiple courses over the two-year period, we include student fixed effects that capture unobserved student characteristics. The within-student design implied by student fixed effects accounts for the reservation status of the student, as well as baseline differences in ability, aptitudes, and socioeconomic backgrounds. Consistent with random assignment of students to classrooms estimates of β_1 are not sensitive to the exclusion of student fixed effects or controlling for or not controlling for a set of student characteristics (see Appendix Table D1).[20]

The starting specification does not control for any faculty characteristics and qualifications to address the question of whether there are any unconditional differences in instructional quality between reservation and general category faculty. The comparison is based on the end result of the reservation or affirmative action hiring policies of the colleges. These policies might lead to hiring less qualified faculty, and the estimate of β_1 from this specification captures the unconditional dif-

[19] Course fixed effects are constructed as a combination of college, department, course and semester fixed effects. Thus, the represent a specific offering of a course for students

[20] Student characteristics include reservation category status, gender, age, mother's education level, and father's education level.

ference in teaching performance on account of those policies. This is potentially the specification of most interest if the goal is to evaluate reservation policies. Another goal is to better understand differences in quality of instruction by reservation status, conditioning on faculty qualifications. We estimate specifications that control for different sets of faculty qualifications. These qualifications include dummy variables for highest educational degree (bachelor's, master's, or PhD), whether they graduated from an elite engineering college, professorial rank (assistant, associate, or full professor), and years of work experience in academia. Conditioning on these qualifications, we check for differences in instructional quality between reservation and general category faculty. The results provide evidence on whether the any observed productivity differential between the two groups of faculty is capturing reservation status per se, or another related characteristic.

4.2 Student-Faculty Interaction Regression Models

We next examine whether there exist "teacher-like-me" effects. To test whether reservation category students perform better when taught by reservation category faculty than with general category faculty, we interact the reservation category status of the student with that of the faculty. The same model also allows us to explore whether general category students do worse with reservation category faculty than with general category faculty. Potential reasons behind this might be resentment about being taught by reservation category faculty, resulting in lower levels of effort in those courses, or learning differences on account of a mismatch in cultural, linguistic, or other backgrounds. We start with the following model:

$$Y_{ikcf} = \alpha + \beta_1 RT_f + \beta_2 RT_f \times RS_i + \gamma_2 T_f + \lambda_k + \lambda_i + \epsilon_{ikcf} \tag{4.2}$$

where RS_i is a dummy variable for the reservation category status of student i, as defined earlier. The student fixed effects λ_i subsume the stand-alone student reservation status indicator RS_i. We estimate this base specification including various sets of faculty characteristics.

When we focus on the question of "teacher-like-me" effects instead of absolute effects we can push the model further by adding faculty fixed effects λ_f, which subsumes the reservation category status indicator for the faculty RT_f and the faculty characteristics T_f. We use variation across courses for faculty to identify these fixed effects. In another specification, we can add classroom fixed effects

λ_c, which in turn subsume both the course fixed effect λ_k and the faculty fixed effect λ_f. As a result, the reservation category status indicator variables RT_f and RS_i, and fixed effects λ_k and λ_f are no longer identified. The final model is specified as:

$$Y_{ikcf} = \alpha + \beta_2 RT_f \times RS_i + \lambda_i + \lambda_c + \epsilon_{ikcf} \tag{4.3}$$

In this case β_2 is identified from comparisons between reservation category and general category students in the same classroom but with different reservation status of faculty.

5 Results

5.1 Reservation Status and Faculty Qualifications

We first examine whether faculty hired through reservation policies have lower qualifications than general category faculty. Lower qualifications may, but do not necessarily, contribute to differences in quality of instruction (Hanushek, Kain, & Rivkin, 2005) between general category and reservation category faculty. Reservation category faculty candidates are in shorter supply and thus chosen from a more restricted labor pool. We explore reservation category vs. general category differences in the population using NSS microdata, as well as among faculty using the nationally representative sample of engineering and technology colleges.

First, our analysis of NSS microdata indicates that among the broader population that belongs to groups that qualify for reservation policies, individuals are much less likely to have a master's degree (the minimum educational credential required to teach at engineering and technology colleges in India), than individuals in the general category population. As reported in Appendix Table A1, less than 2 percent of the reservation category population has a master's degree, compared with nearly 6 percent of the general category population. The percentage of the reservation category population with a master's degree is also lower when conditioning on younger ages, high school degrees or college degrees. These findings suggest that the general labor pool meeting the minimum educational credentials for teaching at a college is smaller for the reservation category population.

Second, using our nationally representative sample of 50 colleges, we present novel findings on the question of whether faculty hired through reservation policies have lower measurable qualifications than general category faculty. There is surprisingly little evidence on this question in the existing literature and from published government reports. Table 5.1 reports average faculty qualifications (educational degrees, professorial rank, and years of experience) by reservation status and the difference between the two.[21] Reservation category faculty are 6 percentage points more likely to be assistant professors and 5 percentage points less likely to be full professors. Consistent with lower professorial ranks, reservation category faculty have about 1 year less of work experience in academia than general category faculty (relative to a base level of 10 years of experience for general category faculty).[22] We also find that reservation category faculty are 7 percentage points less likely to have completed their PhDs, and 6 percentage points more likely to have a master's degree as their highest degree, compared to general category faculty. We also find that reservation category faculty are less likely to have degrees from elite colleges. These new findings on differences in faculty qualifications indicate that reservation category faculty have lower professorial ranks, fewer years of work experience in academia, and lower education levels.[23]

Table 5.1: Faculty Qualifications by Reservation Status at Engineering and Technology Colleges in India

	Reservation Cat. Faculty	General Cat. Faculty	Difference
Assistant professor	0.80	0.74	0.06** (0.03)
Associate professor	0.13	0.14	-0.01 (0.02)
Professor	0.03	0.08	-0.05*** (0.01)
Experience (years)	8.91	10.06	-1.15** (0.49)
Highest degree PhD	0.14	0.21	-0.07*** (0.02)
Highest degree PhD in progress	0.18	0.18	0.00 (0.03)
Highest degree Master's	0.64	0.58	0.06* (0.03)
Degree from elite college	0.26	0.23	0.03 (0.03)
Female	0.40	0.44	-0.04 (0.03)
N	1206	1485	

Notes: Estimates use department-level sampling weights defined across the full national sample of surveyed colleges (50 colleges). The last column reports difference in group means with standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We next explore whether there might be differences in unobservable ability or quality between reservation and general category faculty. In particular, discrimination in the IT labor market against highly-educated reservation category workers (Upadhya, 2007) could limit opportunities and "push" high-ability reservation category workers into faculty positions which are covered by

[21]The patterns are similar for our subsample of 12 colleges with random assignment. We discuss this comparison below when we present results for a balance check using the sample with random assignment.

[22]Within professorial ranks mean years of experience are similar except for within the full professor level where reservation category faculty have less mean experience.

[23]In contrast to these differences, we find similar assignment of reservation category faculty vs general category faculty to courses by term, introductory vs advanced material, and year. See Appendix Table C1.

affirmative action policies. In this case, the average (unobservable) quality of reservation category faculty might even be higher than that of general category faculty, conditioning on working as faculty in engineering and technology colleges. Discrimination in the private labor market might alter quality differentials in non-discriminatory or affirmative action sectors of the labor market such as government or education.

To provide some descriptive evidence on this question, we estimate the differential returns to college for general category and reservation category workers using NSS microdata.[24] The results, presented in Table 5.2 indicate a negative and significant wage gap for workers from the lower caste and social class groups covered by reservation policies across several specifications, and after accounting for differences in education levels, age, and occupation fixed effects. We do not find evidence of a statistically significant difference between the wages of uneducated (i.e, not college graduate) reservation and general category workers after including occupation fixed effects, which is likely due to the strong mapping between caste and occupational guilds, especially for low-skilled, informal sector jobs. However, even controlling for occupations, the wage gap for college-educated workers is large for reservation category workers. Finally, we find that the wage gap between reservation and general category college graduates is significantly larger in private sector jobs, which might push qualified reserved category workers into public sector jobs with affirmative action policies. These results are consistent with the evidence provided by Madheswaran and Attewell (2007), Bertrand et al. (2010), and Mitra (2019).

[24] Reservation-general category population differences in educational and economic outcomes are discussed above and reported in Appendix Table A1.

Table 5.2: Returns to Education by Reservation Status

	(I)	(II)	(III)	(IV)	(V)	(VI)
	Dependent Variable: ln(Weekly Wages in Rupees)					
College degree	1.273***	1.152***	0.497***	0.493***	0.208***	0.596***
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.06)
Res. Category	-0.261***	-0.137***	-0.031*	-0.018	-0.126***	-0.106**
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
College degree × Res. Category	-0.057	-0.140***	-0.152***	-0.154***	0.002	-0.161**
	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)	(0.07)
Age		0.045***	0.042***	0.032***	0.075***	0.046***
		(0.01)	(0.00)	(0.01)	(0.02)	(0.02)
Age^2		-0.000***	-0.000***	-0.000*	-0.001***	-0.000**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female		-0.519***	-0.418***	-0.394***	-0.410***	-0.234***
		(0.02)	(0.02)	(0.02)	(0.03)	(0.07)
Urban		0.441***	0.197***	0.195***	0.286***	0.179***
		(0.03)	(0.02)	(0.02)	(0.03)	(0.04)
Occupation FE	No	No	Yes	Yes	Yes	Yes
Age Range	25-64	25-64	25-64	25-45	25-64	25-64
Job Type	All	All	All	All	Public Sector	Private Sector
N	56241	56241	56241	40856	17843	4636

Notes: Estimates use microdata from the 68th Round of India's National Sample Survey, and are weighted by population using NSS multipliers. The dependent variable is the log-transformation of weekly wages reported by the respondent. The sample only includes respondents reporting non-zero wages. Standard errors are clustered at the district level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

In the end, reservation category faculty may have lower measurable educational credentials and academic ranks, but this does not imply that they are necessarily less qualified to teach students. Discrimination in the private sector might lead high-ability (along unobservable traits) reservation category workers to faculty positions.

5.2 Quality of Instruction among Reservation Category Faculty

We next explore the question of whether there are differences between the quality of instruction provided by reservation category and general category faculty. In attempting to answer this question, there are concerns about selection bias. Reservation category faculty might be assigned to different courses, and have different students choose their classes. Sorting by students and faculty, and differential sorting into courses taught by reservation category faculty potentially contaminate comparisons between reservation category and general category professors teaching the same students. We thus focus the analysis on colleges that randomly assign students to classrooms. Students typically take a fixed set of required courses over the first two years at engineering and technology colleges in India, further limiting the potential for differential selection into courses. Course fixed effects, which are constructed uniquely for each college-department-semester-course combination, account for college and department-specific factors. Student fixed effects account for observable and unobservable baseline differences in student characteristics such as ability, aptitude, and socioeconomic status.

Before turning to the regression results, we present differences in faculty characteristics by reservation status and conduct a balance check for the random assignment of student classrooms to faculty by reservation status for our sample of colleges with random assignment. Table 5.3 reports these results. To explore potential differences between reservation and general category faculty teaching the same courses (but different classrooms) we estimate a separate regression for each faculty characteristic (i.e. row) that includes course fixed effects and a dummy variable indicating the reservation status of the faculty. Column 3 reports the coefficient estimate on this reservation category vs. general category faculty difference, and Column 4 reports the standard error. We find that reservation category faculty have lower professorial ranks, less work experience in academia, and lower education levels in our 12-college subsample, which are similar to the patterns noted above for our national sample.

Table 5.3: Faculty Differences and Balance Checks for the Sample of Colleges with Random Assignment

	Panel A: Faculty			
Faculty characteristics	**Mean**	**SD**	**Res.-Gen. Faculty**	**SE**
Reservation Category	0.39	0.49	1.000	
Assistant professor	0.72	0.45	0.055	0.061
Associate professor	0.18	0.38	0.018	0.043
Professor	0.08	0.27	-0.071	0.043
Experience in years	9.96	6.51	-1.391*	0.793
Highest degree is Masters	0.51	0.50	0.147**	0.074
Highest degree is PhD	0.32	0.47	-0.133***	0.041
Highest degree is PhD in progress	0.15	0.36	-0.023	0.068
Degree from elite college	0.32	0.47	-0.109*	0.063
Female	0.33	0.47	-0.008	0.076
	Panel B: Students			
Student characteristics	**Mean**	**SD**	**Res.-Gen. Faculty**	**SE**
Reservation Category	0.54	0.50	-0.008	0.010
Female	0.44	0.50	-0.002	0.007
Age	17.72	0.80	0.001	0.011
Father attended college	0.50	0.50	0.005	0.010
Mother attended college	0.35	0.48	0.018**	0.008
Baseline math score	0.00	1.00	0.001	0.024
Baseline physics score	0.00	1.00	-0.010	0.025
JEE Main score	68.14	44.33	0.971	0.920
Took JEE Main	0.67	0.47	0.004	0.008

Notes: Means and standard deviations for general category faculty characteristics are reported in Panel A. Means and standard deviations for all sampled students are reported in Panel B. The sample of colleges with random assignment (12 colleges) is used, and the unit of analysis is a student-course. The data capture 2268 students, 501 faculty, 415 courses, and 1277 classrooms. The reservation vs general category differences control for course fixed effects, and corresponding standard errors are clustered at the faculty level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5.3 also reports a balance check for student characteristics. The check suggests that faculty are essentially randomly assigned students to the classrooms that they teach within a given course. Each classroom is a course-section or "classroom" within that course (e.g. Electrical Engineering 1A or Electrical Engineering 1B) and is taught by one faculty. We find no differences in student characteristics in between classrooms taught by reservation category faculty and classrooms taught by general category faculty with the only exception that we find a slightly higher mean value for students having a college-educated mother. The difference, however, is very small. The reservation vs general category faculty differential for student's likelihood of having a college educated mother is 0.018 relative to a mean of 0.35. We have balance on the JEE scores in our sample. We also have balance on an indicator for whether students took the JEE test. As noted below, taking the JEE exam is a positive predictor of student success. Finally, we added the test scores for the baseline tests that we administered in math and physics. For baseline math and physics scores we have balance. We include student fixed effects in the regressions to control for any residual imbalance in these characteristics, as well as any (observed or unobserved) student-level factors.

Table 5.4 reports estimates of Equation 4.1. Specification I only includes the faculty reservation status indicator (Res. Cat. Faculty). We find that reservation category faculty do not teach worse, and in fact teach slightly better than general category faculty. Students in classrooms taught by reservation category faculty have slightly higher grades than students in classrooms taught by general category faculty. The difference is small at 1.44 percentile ranks (scale 1-100) but is statistically significant at the 5% level. Given that the mean percentile rank is 50, this translates into a difference of 3 percent relative to the mean (or 0.05 standard deviations using the standard deviation of 28.9 as noted above).

Table 5.4: Regressions for Student Course Grades Measuring Quality of Instruction, Reservation vs. General Category Faculty

	I	II	III	IV
Res. Cat. Faculty	1.44**	1.52**	1.33**	1.34**
	(0.58)	(0.59)	(0.57)	(0.56)
Associate professor		0.57	1.25	1.27
		(0.75)	(0.83)	(0.82)
Professor		1.46	2.97**	3.18**
		(0.93)	(1.35)	(1.32)
Experience in years		-0.02	-0.02	-0.01
		(0.05)	(0.05)	(0.05)
Highest degree PhD			-2.37**	-2.55**
			(1.19)	(1.17)
Highest degree PhD in progress			-0.75	-0.94
			(0.80)	(0.82)
Degree from elite college			0.37	0.31
			(0.59)	(0.59)
Female				1.09*
				(0.57)
Mean	51.19	51.19	51.19	51.19
N	37767	37716	37716	37716

Notes: The dependent variable is the student course grade measured as the percentile rank in the course (1-100 scale). Grades are provided at the course level and not at the faculty-taught section level. All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student-course. All models also control for student fixed effects and course fixed effects. Standard errors are clustered at the faculty level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The additional specifications reported in Table 5.4 expand the set of controls for faculty characteristics. A pure evaluation of reservation policies might stop at Specification I and not control for any differential characteristics among reservation category faculty resulting from affirmative action policies. The unadjusted coefficient on reservation category faculty on student grades incorporates the possible lower qualifications from hiring quotas. We sequentially add faculty characteristics to move from this policy focused model to one that focuses more on estimating reservation vs general category faculty differences per se. Specification II allows for reservation category faculty to be of different ranks (i.e. assistant, associate and full professor) and years of work experience in higher education. If there was a shortage of engineering faculty in the past, it is likely that engineering and technology colleges need to hire a range of professorial ranks. Thus, some colleges might need to hire reservation category (or general category) faculty at a specific rank such as associate professors. Conditioning on hiring at this level, the reservation policy binds. In any case, we find a similar coefficient on the faculty reservation status indicator variable. The coefficient implies an effect of 1.52 course grade percentile points and is statistically significant at the 5% level.

The next column (Specification III) controls for the education level of the faculty. Interestingly, having a PhD results in lower course grades for students. As shown in Table 5.3, reservation category faculty were less likely to have a PhD. However, even though controlling for this difference works to reduce the coefficient on reservation category faculty, the effect is very minor, and the coefficient remains positive (1.33) and statistically significant at the 5% level. In the final specification reported in Table 5.4 we additionally control for whether the professor is female. The coefficient estimate on reservation category faculty does not change.

All of the reported regressions include student fixed effects. We also estimate regressions that control for student characteristics instead of student fixed effects. We find very similar estimates on the reservation category faculty dummy variable for all four specifications. As an additional check, we find that the results are also very similar after removing the only elite college in the 12-college sample (which only represents 4.8 percent of the total sample).

The unit of observation in the regressions is the student course-grade which implicitly places more weight on larger classrooms. To explore whether our results are partly driven by the influence of larger classrooms, we estimate regressions in which student-course observations are weighted to equalize the influence of all classroom sizes. Specifically, each student course-grade observation is weighted by the inverse of the size of the classroom. Appendix Table D2 reports the results from estimating Equation 4.1 with (inverse) class-size weights attached to each observation. We obtain similar results to those reported in Table 5.4. The similarity of estimates is consistent with most classroom sizes being in a narrow range around 30 students and very few with more than 100 students.

Overall, the results show consistent and robust evidence that reservation category faculty do not provide lower quality instruction to students, and in fact provide slightly higher quality instruction. The conclusion does not depend on whether we directly compare reservation category faculty to general category faculty or control for their lower professorial ranks, less work experience in higher education, and lower levels of education.

5.3 Differences in Time Spent on Teaching Activities and Teaching Practices

Do reservation category faculty devote more time to teaching, which could explain why students in their classes do better? Reservation category faculty might be of lower quality, but put more time into teaching and helping students outside of class time, resulting in similar student performance (i.e. more effort overcomes lower per quality per unit of time). Specifically, do they devote more time and effort to teaching-related activities such as advising students or preparing lessons, which in turn compensates for lower ability? To investigate this question, we run regressions for teaching-related activities focusing on the faculty reservation status indicator coefficient (Table 5.5). We control for course fixed effects, student fixed effects, and the full set of faculty characteristics. We examine weekly hours on advising students, course-related work, lesson planning, teaching class, and tutoring students. We continue to use the student course-grade as the unit of analysis for consistency with the quality of instruction regressions and ability to control for course fixed effects and weight by the number of students taught.[25] Standard errors are clustered at the faculty level to account for the variation of the dependent variable being limited to the faculty level.

[25]Each observation is at the student-course level to weight the results by student contact. Thus, a faculty member teaching only a few students is weighted less than a faculty member teaching hundreds of students in the sample.

Table 5.5: Regressions for Weekly Hours Spent on Various Teaching-Related Activities, Reservation vs General Category Faculty

	Advising Students	Course-Related Work	Lesson Planning	Teaching Classes	Tutoring
Res. Cat. Faculty	-0.40	0.00	0.09	-0.24	-0.10
	(0.30)	(0.48)	(0.92)	(1.25)	(0.30)
Associate professor	-0.09	-2.74**	0.11	-0.20	0.26
	(0.38)	(1.26)	(1.08)	(1.60)	(0.40)
Professor	-0.60	-0.57	-2.28	-1.46	-0.20
	(0.59)	(1.39)	(1.67)	(1.57)	(0.51)
Experience in years	0.01	0.02	-0.16**	0.10	0.04*
	(0.03)	(0.03)	(0.08)	(0.08)	(0.02)
Highest degree PhD	0.58	3.75**	-0.54	0.42	0.58
	(0.49)	(1.64)	(1.39)	(1.17)	(0.44)
Highest degree PhD in progress	0.52	-0.45	-0.65	1.15	0.43
	(0.54)	(0.56)	(0.97)	(1.11)	(0.36)
Degree from elite college	-0.23	-1.81**	0.69	-0.83	-0.72**
	(0.44)	(0.88)	(0.99)	(1.04)	(0.33)
Female	-0.10	-0.97	-0.75	-0.33	0.20
	(0.22)	(0.68)	(0.87)	(1.01)	(0.26)
Mean	3.33	2.98	7.35	11.02	2.82
N	37687	37789	37789	37789	37789

All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student-course. All models control for student fixed effects and course fixed effects, and standard errors are clustered at the faculty level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The estimates reported in Table 5.5 are small in magnitude and not statistically different from 0. According to these results, reservation category faculty do not spend more time on course-related work or on lesson planning, or helping students outside of the classroom through advising or tutoring.[26]

We also ask faculty a question about about weekly hours spent teaching their classes. This variable provides a useful check that reservation category faculty are not teaching for different amounts of time than general category faculty. Classrooms within courses are scheduled for the same amount of time, and thus this question provides a quality check on both reported hours worked on activities and that reservation category and general category faculty are being compared to each other for the same courses. We find no evidence that reservation category faculty spend more time teaching their courses than general category faculty.

We also surveyed faculty on their classroom-specific pedagogical practices including a set of Teaching Practices Inventory (TPI) measures based on Wieman and Gilbert (2014). These TPI measures provide a test of whether there are potential differences in the types of teaching practices used in

[26]We also collect information on whether students received tutoring and do not find any difference based on the percentage of courses taken with reservation category faculty by students.

classrooms. The use of active learning techniques in the classroom, for example, is a growing teaching practice and might explain instructional quality differences between reservation and general category faculty.[27] Estimates reported in Table 5.6 do not indicate that reservation category faculty and general category faculty are implementing different teaching practices. The findings suggest that the higher instructional quality found for reservation category faculty is not due to the use of different teaching practices instead of underlying quality differences.[28]

Table 5.6: Regressions for Use of Teaching Practices Inventory Measures, Reservation vs. General Category Faculty

	In-class features and activities	Assignments	Feedback and testing	Collaboration
Res. Cat. Faculty	-0.23	-0.20	-0.13	-0.21
	(0.35)	(0.26)	(0.38)	(0.22)
Associate professor	0.10	0.16	0.46	-0.17
	(0.43)	(0.30)	(0.52)	(0.26)
Professor	0.81	0.04	1.10	-0.10
	(0.55)	(0.45)	(0.69)	(0.31)
Experience in years	0.02	0.04**	0.08**	0.04**
	(0.02)	(0.02)	(0.03)	(0.02)
Highest degree PhD	-0.21	-0.46	-0.63	-0.30
	(0.51)	(0.32)	(0.54)	(0.32)
Highest degree PhD in progress	1.16**	-0.04	1.30***	0.28
	(0.45)	(0.30)	(0.40)	(0.23)
Degree from elite college	-0.31	0.34	-0.41	-0.01
	(0.30)	(0.27)	(0.33)	(0.21)
Female	-1.11***	0.33	-0.09	0.25
	(0.35)	(0.24)	(0.35)	(0.19)
Mean	9.65	3.55	8.28	4.20
N	37970	37970	37970	37970

All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student-course. All models control for student fixed effects and course fixed effects, and standard errors are clustered at the faculty level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.4 Additional Measures of Teaching Productivity

We explore several additional measures of teaching productivity by faculty. Productivity might differ between reservation category and general category faculty, in a way that is not captured by effects on immediate educational outcomes such as course grades. Estimates of effects on course grades, for example, might capture differences in "teaching to the test" instead of learning outcomes

[27] Studies report that using pedagogical practices such as active and collaborative learning positively impacts student performance (Freeman et al., 2014; Hoellwarth & Moelter, 2011; Porter, Bailey Lee, & Simon, 2013).

[28] As a robustness check, we explore whether the main results for faculty effects on student course grades are sensitive to the inclusion of measures of teaching time and teaching practices. We estimate regressions for student course grades in which we individually add the contemporaneous teaching time and teaching practices variables to the main specifications reported in Table 5.4. We find that the coefficients for the faculty reservation status indicator variable are not sensitive to the inclusion of these variables.

that extend beyond that course (Carrell & West, 2010).

We first examine faculty effects on follow-on courses. An effective instructor of a course might have positive spillovers on how students do in subsequent courses in the same subject or in general. We measure follow-on courses in two ways. First, we regress student course grades on prior term average faculty characteristics. Second, we measure prior average faculty characteristics over all precursor courses taken by a student in the previous term for that specific course. In this sense, the second definition is a subset of the first definition. In both specifications, the percentage of classes taken with reservation category faculty is included when there are multiple prior courses instead of only one. Table 5.7 reports estimates. We find no evidence of a negative reservation category faculty effect on follow-on course grades.

Table 5.7: Regressions for Follow-on Course Grades and Test Scores, Reservation vs. General Category Faculty

	I Follow-On Grade (Semester)	II Follow-On Grade (Course)	III Math Test Score	IV Physics Test Score
Res. Cat. Faculty	0.654	0.850	0.020	0.032
	(1.485)	(1.017)	(0.031)	(0.030)
Associate professor	5.535*	0.428	-0.063**	0.002
	(2.986)	(1.631)	(0.026)	(0.045)
Professor	8.933**	2.692	-0.043	0.024
	(4.007)	(2.552)	(0.039)	(0.068)
Experience in years	-0.204	0.128	0.003*	0.004
	(0.186)	(0.122)	(0.002)	(0.003)
Highest degree PhD	-2.372	-4.592**	0.068*	-0.046
	(3.805)	(1.804)	(0.041)	(0.039)
Highest degree PhD in progress	1.395	0.669	0.049**	-0.043
	(2.518)	(1.507)	(0.025)	(0.042)
Degree from elite college	4.847*	-0.354	0.056*	-0.005
	(2.672)	(1.660)	(0.028)	(0.033)
Female	0.809	-0.897	0.006	0.023
	(1.720)	(1.151)	(0.019)	(0.027)
Student controls	FE	FE	Yes	Yes
Mean	51.84	51.67	-0.002	-0.01
N	23218	11740	974	983

Notes: The dependent variables are (I) grade in a follow-on course based on average faculty characteristics in one prior semester, (II) grade in a follow-on course based on average faculty characteristics for *related courses* in one prior semester, (III) standardized score for math endline test, and (IV) standardized score for physics endline test. For Specifications III and IV, Res. Cat. faculty is the percentage of reservation category faculty who taught all prior courses taken by the student. The Res. Cat. faculty variable is rescaled to capture the effect of changing the reservation category faculty percentage by 10 percentage points (e.g. from 0.50 to 0.60). Student controls include reservation category status, gender, age, and parents' education. All models are run for the sample with random assignment (12 colleges). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5.7 also reports faculty effects for math and physics tests which further capture whether students increase general engineering-related knowledge and become more effective learners in future courses. We administered and proctored our own tests in math and physics at the end of two years.[29] Baseline test scores are included as additional controls and faculty characteristic effects are scaled so that they can be interpreted as changing the characteristic by 10 percentage points. We find no productivity differences between reservation category faculty and general category faculty in either math or physics test scores.

We examine two additional measures of faculty productivity that capture course attendance and drop outs. Table 5.8 reports estimates. In Specification I, we measure course attendance by the average daily hours attending classes (mean=6.2). We do not find evidence of a difference between reservation category and general category faculty.[30] Second, we examine administrative information on dropouts by the end of the second year. Very few students drop out of engineering colleges in the first two years (mean=0.01) or in the next two years for that matter (as we show below). We also do not find any difference between reservation category and general category faculty in affecting dropout rates among students (Table 5.8, Specification II).[31]

Faculty might inspire interest in graduate school and research. We next examine whether there are productivity differences on graduate school aspirations and research work opportunities. Specifications III and IV of Table 5.8 report estimates for graduate student plans and research work with faculty, respectively. We find no evidence of differential effects by reservation status.

Focusing on the first two years of the program has the advantage of capturing immediate productivity effects, the period of random assignment of students to classrooms, and rules out the possibility of estimates being confounded by dynamic accumulation effects. As part of the project, however, we collected data on a few longer-term educational outcomes measured at the end of the four-year programs for a second cohort of students. We combined survey information with administrative information to capture major-specific test scores, graduate school plans, and expected graduation with a degree. We first examine the characteristics and test for balance for this separate cohort of students (Appendix Table E1). The average characteristics of students and faculty are similar. One difference is that this cohort of students is on average two years older, which is consistent with

[29] The tests were taken by a random subset (50%) of the students in the sample.

[30] We collected information on whether students received tutoring and found no difference by reservation status of faculty.

[31] We find that no students in our sample switch majors in the first two years and only 1 student in the sample switches in the next two years.

Table 5.8: Regressions for Additional Educational Outcomes, Reservation vs. General Category Faculty

	I Hours Attended	II Dropout	III Plans for Graduate School	IV Research Assistance
Res. Cat. Faculty	0.049	-0.000001	0.015	-0.006
	(0.054)	(0.000002)	(0.016)	(0.006)
Associate professor	-0.033	0.000000	0.019	0.007
	(0.067)	(0.000001)	(0.020)	(0.007)
Professor	0.021	-0.000005	0.005	-0.005
	(0.077)	(0.000015)	(0.027)	(0.009)
Experience in years	0.002	0.000000	-0.001	-0.000
	(0.003)	(0.000000)	(0.001)	(0.000)
Highest degree PhD	-0.053	0.000002	0.005	0.002
	(0.061)	(0.000006)	(0.027)	(0.008)
Highest degree PhD in progress	-0.034	0.000001	0.010	-0.007
	(0.056)	(0.000003)	(0.016)	(0.006)
Degree from elite college	0.002	-0.000000	-0.016	-0.009*
	(0.047)	(0.000001)	(0.018)	(0.005)
Female	0.024	0.000000	0.015	-0.005
	(0.048)	(0.000001)	(0.015)	(0.005)
Student controls	Yes	Yes	Yes	Yes
Mean	6.18	0.01	0.61	0.21
N	3140	1965	2156	2134

Notes: The dependent variables are (I) hours per week spent attending classes, (II) whether a student dropped out, (III) whether the student aspired to attend graduate school after their program, and (IV) whether the student assisted a professor with their research. Res. Cat. faculty is the percentage of reservation category faculty who taught courses taken by the student, and is rescaled to capture the effect of changing the reservation category faculty percentage by 10 percentage points (e.g. from 0.50 to 0.60). The coefficients from Specification II are the marginal effects from a probit model between the dropout (0/1) outcome and the listed covariates. Student controls include reservation category status, gender, age, parents' education, and math and physics baseline z-scores. All models are run for the sample with random assignment (12 colleges), where each observation is a student-test pair (with multiple observations for students who took both physics and math baseline and endline tests). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

the baseline and follow-up surveys being conducted two years later in their studies. We also find balance on all of the student characteristics. Overall, this additional cohort of students does not appear different or face different faculty characteristics than our main cohort of students for which we have course grades.

Using this cohort of students, we examine scores on tests we administered and proctored at the end of year 4 in major-specific skills, reported in Table 5.9. Faculty characteristics including reservation category status are calculated over all courses taken in the first two years for each student. We find no differential effects by the reservation category faculty percentage for either endline test score (Specifications I and II). The results for electric engineering and computer science test scores measured at the end of year 4 for this second cohort of students are consistent with what we find for math and physics test scores measured at the end of year 2 for our main cohort of students.

Table 5.9: Regressions for Additional Educational Outcomes, Reservation vs. General Category Faculty Using the Second Cohort of Students

	I EE Test (Year 4)	II CS Test (Year 4)	III Expected Graduation (Year 4)	IV Plans for Graduate School (Year 4)
Res. Cat. Faculty	-0.029	-0.030	-0.00007	0.006
	(0.029)	(0.048)	(0.00011)	(0.012)
Associate professor	-0.183***	0.020	-0.00002	0.026
	(0.054)	(0.071)	(0.00023)	(0.020)
Professor	-0.343***	0.238*	0.00022	0.017
	(0.108)	(0.123)	(0.00023)	(0.034)
Experience in years	0.004*	-0.009	-0.00001	-0.001
	(0.003)	(0.007)	(0.00011)	(0.001)
Highest degree PhD	0.137**	-0.090	0.00005	0.027
	(0.063)	(0.103)	(0.00022)	(0.023)
Highest degree PhD in progress	0.071	0.111	-0.00010	0.008
	(0.053)	(0.080)	(0.00015)	(0.020)
Degree from elite college	0.000	0.107	-0.00007	0.015
	(0.033)	(0.072)	(0.00010)	(0.014)
Female	0.034	0.015	0.00018**	0.019
	(0.046)	(0.052)	(0.00009)	(0.015)
Student controls	Yes	Yes	Yes	Yes
Mean	0.00	-0.03	0.99	0.51
N	1060	510	2247	2083

Notes: The dependent variables are measured at the end of year 4 and are (I) standardized test score for the electrical engineering (EE) test, (II) standardized test score for the computer science (CS) test, (III) whether the student expected to graduate, and (IV) whether the student aspired for graduate school after completing their program. Res. Cat. faculty is the percentage of reservation category faculty who taught courses taken by the student, and is rescaled to capture the effect of changing the reservation category faculty percentage by 10 percentage points (e.g. from 0.50 to 0.60). Student controls include gender, age, and parents' education. The coefficients from Specification III are the marginal effects from a probit model between the expected graduation (0/1) variable and the listed covariates. All models are run on the second cohort of students for the sample with random assignment (12 colleges), where each observation is a student. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We also examine whether students in this cohort expect to graduate with a degree at the end of year 4. We use administrative data as well as survey data to measure expected graduation. Given the proximity to finishing their degree this measure collected at the end of year 4 is likely to be an extremely accurate predictor of actual graduation with an engineering degree. We use administrative information on their status at the end of year 4. Students who are on academic leave, detained, dropped out, expelled, left the college, medical leave, or stopped paying in the system are coded as not expected to graduate. The use of this variable then builds on what we find when we examine drop outs for the main cohort of students from the beginning of year 1 to the end of year 2. We find that a very high percentage of students expect to graduate with an engineering degree (98.9 percent). We run regressions for expected graduation using this cohort of students and find no differential effect for reservation category faculty percentage on expected graduation. We report these new results in Table 5.9, Specification III.

Finally, for this cohort of students we ask the question about whether they plan on going to graduate school. Roughly half of students at the end of year 4 report planning on going to graduate school. Regressions for graduate school plans as a dependent variable do not reveal differential effects by the reservation category of faculty. We report these new estimates in Table 5.9, Specification IV.

Overall, the results for the wide range of longer-term educational outcomes and using two different cohorts of engineering students are consistent with what we find for the immediate effects on course grades. We find no evidence that reservation category faculty are less productive than are general category faculty.

5.5 Research Productivity

Engineering and technology colleges in India have not traditionally placed an emphasis on research productivity among their faculty (i.e. similar to the typical or representative college in the U.S. which are not research universities). Outside of the elite institutions such as the Indian Institutes of Technology (IITs), the primary basis for promotions and evaluations is a combination of experience and degree qualifications (see AICTE, 2010).[32] However, some emphasis has been placed recently on research productivity. We analyze whether reservation category faculty publish less than general category faculty. We focus on two measures of research productivity in terms of publishing. We examine differences between reservation and general category faculty in: (a) number of publications per year, and (b) number of international journal publications per year. The number of publications is defined as the total number of published academic international journal articles, domestic journal articles, monographs, and edited volumes.

Table 5.10 reports estimates from regressing the number of publications per year on the faculty reservation status indicator variable and additional faculty characteristics. Since we are not focusing on instructional quality (where there are concerns over student sorting) we use the full 50-college sample and faculty as the unit of analysis for these regressions. We report a set of specifications that ranges from an unconditional comparison between reservation and general category faculty to a comparison that controls for the lower professorial ranks and education levels of reservation category faculty. We find no evidence that reservation category faculty publish fewer articles than general category faculty. On average, faculty at engineering and technology colleges in India produce 2.4 publications per year. The point estimate on reservation category faculty is small and precisely estimated. Controlling for the lower likelihood of having a PhD and lower likelihood of coming from an elite college among reservation category faculty does not change the result (Specification II). Our results are robust to the inclusion of all faculty characteristics and gender of the faculty (Specifications III and IV).

[32] Seniority and qualifications factor strongly into promotions. For example, an Assistant Professor with a PhD is eligible for a higher pay grade after four years of service, and one without a PhD is eligible for a higher pay grade after six years of service (see AICTE, 2010). Conditional on a vacancy being available, a candidate with more years of experience is typically granted the promotion.

Table 5.10: Regressions for Number of Publications per Year, Reservation Category vs. General Category Faculty using the National Sample

	I	II	III	IV
Res. Cat. Faculty	-0.12	0.07	0.09	0.06
	(0.12)	(0.10)	(0.10)	(0.11)
Associate professor		0.63***	0.16	0.17
		(0.18)	(0.20)	(0.20)
Professor		2.49***	1.54***	1.51***
		(0.37)	(0.39)	(0.39)
Experience in years		0.07***	0.05***	0.05***
		(0.01)	(0.01)	(0.01)
Highest degree PhD			1.66***	1.67***
			(0.21)	(0.21)
Highest degree PhD in progress			0.69***	0.69***
			(0.14)	(0.14)
Degree from elite college			-0.06	-0.06
			(0.14)	(0.14)
Female				-0.20**
				(0.10)
Mean	2.4	2.4	2.4	2.4
N	2691	2685	2680	2679

Notes: The regressions use department-level sampling weights, and are run at the faculty level for the national sample (50 colleges). All specifications include college and department fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Not all publications are of the same quality and may demand a different amount of effort on the part of the faculty. We attempt to mitigate the noise from publication quality by repeating our analyses using only publications in international academic journals. Table 5.11 reports the same set of specifications as those reported in Table 5.10 but using the number of publications in international journals as the dependent variable. The mean level of publications drops from 2.4 publications per year to 0.98 publications per year when including only publications in international journals. For these more rigorous and potentially more time-consuming publications we also do not find evidence that reservation category faculty are publishing less than general category faculty. The findings are not sensitive to whether faculty qualifications are included in the regressions or not.

Table 5.11: Regressions for Number of International Publications per year, Reservation vs General Category Faculty using the National Sample

	I	II	III	IV
Res. Cat. Faculty	-0.07	0.03	0.04	0.04
	(0.07)	(0.07)	(0.06)	(0.07)
Associate professor		0.40***	0.19**	0.19**
		(0.11)	(0.10)	(0.10)
Professor		1.60***	1.18***	1.17***
		(0.28)	(0.28)	(0.27)
Experience in years		0.02***	0.01**	0.01**
		(0.01)	(0.01)	(0.01)
Highest degree PhD			0.73***	0.74***
			(0.11)	(0.11)
Highest degree PhD in progress			0.28***	0.28***
			(0.06)	(0.06)
Degree from elite college			-0.08	-0.08
			(0.07)	(0.07)
Female				-0.06
				(0.05)
Mean	0.98	0.98	0.98	0.98
N	2691	2685	2680	2679

Notes: The regressions use department-level sampling weights, and are run at the faculty level for the national sample (50 colleges). All specifications include college and department fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We also collected information on whether these papers were published in journals covered by impact factor indices. We collected information from journals covered in the Science Citation Index (SCI), Engineering Index (EI) and Social Sciences Citation Index (SSCI). Publications covered by these indices are considered top-tier in India because they have measured impact factors. The new results are reported in Appendix Table F1. As expected, faculty are publishing fewer articles on average in these journals. Among the average number of publications of roughly 1 per year in international journals, an average of 0.53 articles are published in SCI, EI or SSCI journals. We find that there is no difference between reservation category and general category faculty in the number of impact factor indexed publications.

The main course grade results are also robust to the inclusion of these two measures of publications. We estimate regressions for course grades in which we individually add the contemporaneous publications outcome variables to the main specifications reported in Table 5.4. We find that the reservation category faculty coefficients are not sensitive to the inclusion of the number of publications or number of international publications.

Another measure of research productivity is whether faculty members are actively obtaining funding. We collected information on whether faculty received funding from various sources such as government agencies, private foundations, donors, or industrial partners. We find that receiving funding is not common at engineering and technology colleges in India, with only 13 percent of faculty receiving funding over the two-year period. Table 5.12 reports results from regressions for funding received by faculty. We do not find evidence that reservation category faculty are less likely to obtain funding than general category faculty. Estimates are not sensitive to controlling for professorial ranks and educational levels.

Table 5.12: Regressions for Funding Received, Reservation vs. General Category Faculty using the National Sample

	I	II	III	IV
Res. Cat. Faculty	-0.01	-0.00	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Associate professor		0.03	0.01	0.01
		(0.02)	(0.02)	(0.02)
Professor		0.14***	0.11***	0.10**
		(0.04)	(0.04)	(0.04)
Experience in years		0.00*	0.00	0.00
		(0.00)	(0.00)	(0.00)
Highest degree PhD			0.05**	0.05**
			(0.02)	(0.02)
Highest degree PhD in progress			0.00	0.00
			(0.01)	(0.01)
Degree from elite college			-0.03**	-0.03**
			(0.01)	(0.01)
Female				-0.02*
				(0.01)
Mean	0.13	0.13	0.13	0.13
N	2691	2685	2680	2679

Notes: The dependent variable is any research funding received at college (0/1). The regressions use department-level sampling weights, and are run at the faculty level for the national sample (50 colleges). All specifications include college and department fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Reservation policies might directly affect government-provided grants. We checked this by separating government funding sources from private funding sources. We find that 10 percent of faculty receive government funds and 3 percent of faculty receive private funds. We estimated two separate sets of regressions and report these in new Appendix Table F2 and Table F3. For both funding sources, we find no difference between reservation category and general category faculty in the receipt of grants.

As a robustness check, we also estimate publication and funding regressions using the sample of colleges with random assignment and the student-course as the unit of observation (Appendix Table F4). We find similar results for the reservation category faculty coefficient. The main exception is that we find a negative and statistically significant coefficient (-0.31) for reservation category faculty in the international publications regression. Given the lack of finding a negative effect for the broader measure of publications and the narrower measure of international publications with impact factor indices we do not put too much weight on the one negative coefficient. Our preferred results from the larger nationally representative sample consistently do not show a negative effect and the analyses of faculty productivity for publications, grants and administrative work does not need the random assignment of students to classrooms.

5.6 Service and Administrative Work

The third main job requirement of faculty is administrative service. We collected data on whether each faculty member held an administrative position in their department or at the college. Roughly one-quarter of faculty hold an administrative position. Table 5.13 reports results from regressions for whether the faculty member held an administrative position at the time of the follow-up survey. For our national sample, we do not find that reservation category faculty are less likely to hold an administrative position (although we find marginal significance without controlling for faculty qualifications). Controlling for professorial rank, experience, education, and gender we find no difference in administrative positions held.

Table 5.13: Regressions for Administrative Positions Held, Reservation vs. General Category Faculty using the National Sample

	I	II	III	IV
Res. Cat. Faculty	-0.05*	-0.02	-0.01	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)
Associate professor		0.08	0.07	0.08*
		(0.05)	(0.05)	(0.05)
Professor		0.28***	0.26***	0.25***
		(0.06)	(0.06)	(0.06)
Experience in years		0.02***	0.02***	0.02***
		(0.00)	(0.00)	(0.00)
Highest degree PhD			0.05	0.06
			(0.04)	(0.04)
Highest degree PhD in progress			0.06	0.06
			(0.04)	(0.04)
Degree from elite college			-0.02	-0.02
			(0.03)	(0.03)
Female				-0.10***
				(0.02)
Mean	0.28	0.28	0.28	0.28
N	2686	2685	2680	2679

Notes: The dependent variable is administrative position held at college (0/1). The regressions use department-level sampling weights, and are run at the faculty level for the national sample (50 colleges). All specifications include college and department fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6 Academic Performance of Reservation Category Students

The qualification thresholds or cutoffs in relevant qualifying exams for university admissions are typically lower for students belonging to reservation category groups. For instance, in 2022, the range of reservation group-based differences in cutoffs for the Joint Entrance Examination (JEE) for engineering colleges varied between 21 points and 62 points on the JEE points scale (The Indian Express, 2022). Although these differences have been well documented, we provide new estimates of family background, course performance, and endline test scores differences by reservation status of students in engineering and technology colleges in India. Our estimates of course performance and endline test scores are novel in that we have random assignment of students to classrooms. In our estimation framework, we also make comparisons between reservation and general category students in the same courses and with the same faculty.

Table 6.1 reports estimates of student and family background characteristics from our national sample. In addition to reporting reservation and general category student means, the last column reports differences in group means with standard errors in parentheses. Reservation category students are from less-educated families on average: both fathers' and mothers' education levels are lower. The differences in parental education are large at nearly 20 percentage points. Reservation category students, however, are similar in terms of proportion female and by age.

Table 6.1: Reservation and General Category Student Differences in Engineering and Technology Colleges in India

	Reservation Category Students	General Category Students	Difference	Sample size
Female	0.41	0.40	0.01 (0.01)	20117
Age (years)	18.92	18.99	-0.07* (0.04)	17492
Father attended college	0.40	0.58	-0.18*** (0.01)	20062
Mother attended college	0.27	0.46	-0.19*** (0.01)	20059
JEE Main score	69.33	79.06	-9.73*** (1.21)	10259
Baseline math score	-0.10	0.12	-0.22*** (0.03)	8743
Baseline physics score	-0.10	0.12	-0.22*** (0.03)	8739
N	9619	10501		20120

Notes: Estimates use department-level sampling weights defined across the full national sample of surveyed colleges (50 colleges). The last column reports difference in group means with standard errors in parentheses. JEE Main score can range between -120 (as students received a penalty for incorrect answers) and 360. Baseline math and physics scores are z-scores standardized across all respective test takers. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6.1 also reports reservation versus general category student differences in test scores. We collected information on two sets of test scores. First, we administered and proctored our own math and physics exams at baseline to compare preparation and different admissions standards. We also collected information on widely used JEE Main scores. Admission to top engineering and technology colleges in India requires achieving top scores in the JEE exams. However, not all students take the exams if they do not apply to the top colleges. Table 6.1 reports reservation and general category scores on all three sets of tests. Consistent with different admission standards, we find that reservation category students have lower JEE Main scores. About 50 percent of all aspiring students take the JEE exam; some students take local/state-based exams instead. For those students who take the exam we find that reservation category students score 10 points lower on average than general category students. Similar to these differences we find using our own math and physics scores that reservation students have lower scores. The differentials are large: reservation students score 0.22 of a standard deviation lower than general category students in baseline math and physics.[33]

[33] We administer math and physics tests to half of all students in our sample.

We next turn to estimating regressions for student course grades using the sample of colleges with random assignment. For the first time in the literature, we estimate reservation-general category student differences using random assignment to classrooms. Students cannot choose their instructors, thereby removing potential selection biases from those choices. We can rule out differential sorting by students to improve performance in classes. We report our estimates in Table 6.2. We start with a specification that does not control for any other student characteristics (Column 1). We find that reservation category students score 5 percentile points lower in their courses than general category students. Controlling for parental education, age and female only reduces the point estimate slightly (Specification II). In Specification III we control for our standard set of faculty characteristics. We find a similar coefficient for reservation category students. Finally, we control for faculty fixed effects in Specification IV and also find that reservation category students score 5 percentiles lower in courses.

Table 6.2: Regressions for Student Course Performance by Student Reservation Category Status

	I	II	III	IV
Res. Cat. Student	-5.70***	-4.92***	-4.93***	-4.97***
	(0.30)	(0.30)	(0.30)	(0.30)
Female		11.60***	11.62***	11.66***
		(0.38)	(0.38)	(0.38)
Age (years)		-0.26	-0.27	-0.23
		(0.21)	(0.21)	(0.21)
Father attended college		1.19***	1.17***	1.18***
		(0.33)	(0.33)	(0.33)
Mother attended college		0.07	0.09	-0.00
		(0.35)	(0.35)	(0.35)
Faculty controls	No	No	Yes	No
Faculty FE	No	No	No	Yes
Mean	51.19	51.19	51.19	51.19
N	37894	37703	37477	37703

Notes: All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student-course. All models also control for course fixed effects. Faculty controls include reservation category status, professor rank, experience, highest degree, elite college, and gender. Missing values for student age (12.4%) are included with a missing value indicator. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6.3: Regressions for Student Course Performance by Student Reservation Category Status Controlling for JEE Scores

	I	II	III
Res. Cat. Student	-7.53***	-6.47***	-4.88***
	(0.40)	(0.41)	(0.30)
Female	8.74***	8.85***	11.61***
	(0.54)	(0.54)	(0.38)
Age (years)	0.15	0.10	-0.19
	(0.30)	(0.30)	(0.21)
Father attended college	1.23***	1.06**	0.55*
	(0.44)	(0.43)	(0.33)
Mother attended college	-0.53	-0.85*	-0.27
	(0.45)	(0.45)	(0.35)
JEE Main score		0.08***	
		(0.01)	
Took JEE Main			7.74***
			(0.34)
Faculty controls	Yes	Yes	Yes
Mean	51.19	51.19	51.19
N	19888	19888	37477

Notes: All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student-course. All models also control for course fixed effects. Faculty controls include reservation category status, professor rank, experience, highest degree, elite college, and gender. Missing values for student age (12.4%) are included with a missing value indicator. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We next explore course grade differentials conditioning on JEE scores. Table 6.3 reports estimates from a regression that controls for JEE scores. Conditioning on taking the test we lose roughly half of the sample. Thus, Specification I reports a regression that uses the same subsample of test takers for comparability of the coefficients for reservation category students. Reservation category students score 7.5 percentiles lower in the restricted subsample of test takers. After controlling for JEE scores, the differential drops to 6.5 percentiles but remains large. As expected, JEE scores are important predictors of course performance; we find a large positive coefficient on the JEE score. Instead of focusing on scores we instead control for taking the JEE exam by including an indicator variable. We find that the reservation category student coefficient does not change (compared with the full sample coefficient of -4.97 reported in Specification IV of Table 6.2).

Our math and physics tests were administered to half of all the students in the sample, randomly determined. Focusing on this subsample of students we estimate regressions for student course grades that control for baseline math and physics scores. Table 6.4 reports estimates from these regressions. The starting point without these test scores indicates a reservation-general category student differential of 6.35 percentiles. Controlling for these test scores we find that the reservation category student coefficient becomes only slightly smaller. We continue to find that reservation category students have course grades that are 4.6 to 5.7 percentiles lower than general category students.

Table 6.4: Regressions for Student Course Performance by Student Reservation Category Status Controlling for Baseline Math and Physics Test Scores

	I	II	III	IV
Res. Cat. Student	-6.35***	-4.80***	-5.67***	-4.56***
	(0.44)	(0.43)	(0.44)	(0.43)
Female	11.45***	12.08***	11.43***	12.00***
	(0.55)	(0.55)	(0.55)	(0.55)
Age (years)	-0.49	-0.55*	-0.66**	-0.65**
	(0.31)	(0.31)	(0.31)	(0.31)
Father attended college	0.51	0.19	0.38	0.15
	(0.48)	(0.48)	(0.48)	(0.48)
Mother attended college	-0.28	-0.66	-0.37	-0.68
	(0.50)	(0.49)	(0.50)	(0.49)
Baseline math z-score		5.45***		4.91***
		(0.23)		(0.24)
Baseline physics z-score			3.42***	1.99***
			(0.24)	(0.25)
Faculty controls	Yes	Yes	Yes	Yes
Mean	51.19	51.19	51.19	51.19
N	17791	17791	17791	17791

Notes: All models are run on the sample of with random assignment (12 colleges), where each observation is a student-course. All models also control for course fixed effects. Faculty controls include reservation category status, professor rank, experience, highest degree, elite college, and gender. Missing values for student age (12.4%) are included with a missing value indicator. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We also examine reservation vs. general category student differences in endline test scores in math and physics tests that we administered. Table 6.5 reports estimates using the endline test score in math as the dependent variable. We find that reservation category students score substantially lower than general category students on our math test. The differential in math test scores only becomes slightly smaller after controlling for differences in baseline math scores (Specification II). Similarly, controlling for parental education and other student characteristics does not eliminate the disparity in endline test scores.

Table 6.5: Regressions for Student Endline Math Test Scores by Student Reservation Category Status

	I	II	III	IV
Res. Cat. Student	-0.401***	-0.334***	-0.318***	-0.309***
	(0.062)	(0.061)	(0.062)	(0.061)
Baseline math z-score		0.255***	0.263***	0.254***
		(0.037)	(0.038)	(0.039)
Female			0.214***	0.198***
			(0.068)	(0.067)
Age (years)			-0.086**	-0.082*
			(0.043)	(0.044)
Father attended college			-0.037	-0.021
			(0.070)	(0.071)
Mother attended college			0.027	0.027
			(0.072)	(0.073)
Faculty controls	No	No	No	Yes
Mean	0.639	0.639	0.639	0.639
N	988	988	984	984

Notes: All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student. All models also control for course fixed effects. Faculty controls include reservation category status, professor rank, experience, highest degree, elite college, and gender. Missing values for student age (12.4%) are included with a missing value indicator. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6.6 report estimates for regressions using our endline physics score as the dependent variable. We also find that reservation category students score lower on the physics test and the differential remains large after controlling for baseline physics scores and student characteristics.

Table 6.6: Regressions for Student Endline Physics Test Scores by Student Category Reservation Status

	I	II	III	IV
Res. Cat. Student	-0.243***	-0.212***	-0.195***	-0.197***
	(0.050)	(0.048)	(0.050)	(0.050)
Baseline physics z-score		0.149***	0.148***	0.140***
		(0.029)	(0.029)	(0.029)
Female			0.008	0.003
			(0.060)	(0.060)
Age (years)			-0.039	-0.038
			(0.035)	(0.035)
Father attended college			0.042	0.055
			(0.056)	(0.055)
Mother attended college			0.021	0.021
			(0.059)	(0.059)
Faculty controls	No	No	No	Yes
Mean	0.31	0.31	0.31	0.31
N	987	987	983	983

Notes: All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student. All models also control for course fixed effects. Faculty controls include reservation category status, professor rank, experience, highest degree, elite college, and gender. Missing values for student age (12.4%) are included with a missing value indicator. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The evidence for students is clear. We first confirm that reservation category students are admitted with lower test scores as measured by both the JEE scores and tests administered by us at the beginning of the study. Further, we find that reservation category students have lower course grades and lower endline test scores than general category students. The differentials do not disappear after we control for baseline test scores, JEE scores, and student characteristics including parental education.

We also examine whether reservation category students experience lower longer-term educational outcomes. Table 6.7 reports estimates for class attendance, dropout, graduate school plans, and research work with professors. We find that reservation category students have similar dropout rates and plans for graduate school, but interestingly, have higher levels of class attendance and research work with professors than general category students.

Using the second cohort of students for the sample of colleges with random assignment (12 colleges), we also examine outcomes measured at the end of year 4. We find that reservation category students have lower computer science and electrical engineering test scores (reported in Appendix Table E2). We do not find, however, that reservation category students have a lower likelihood

Table 6.7: Regressions for Additional Educational Outcomes by Student Reservation Category Status

	I Hours Attended	II Dropout	III Plans for Graduate School	IV Research Assistance
Res. Cat. Student	0.606***	0.000001	-0.027	0.037**
	(0.162)	(0.000004)	(0.023)	(0.018)
Female	0.540***	0.000000	0.012	-0.053**
	(0.188)	(0.000002)	(0.026)	(0.021)
Age (years)	0.008	0.000001	0.016	0.000
	(0.125)	(0.000002)	(0.015)	(0.013)
Father attended college	-0.023	0.000000	0.043*	-0.075***
	(0.181)	(0.000001)	(0.025)	(0.019)
Mother attended college	-0.300	0.000000	0.028	0.022
	(0.192)	(0.000001)	(0.026)	(0.020)
Faculty controls	Yes	Yes	Yes	Yes
Mean	6.18	0.01	0.61	0.21
N	3140	1965	2156	2134

Notes: The dependent variables are (I) hours per week spent attending classes, (II) whether a student dropped out, (III) whether the student aspired to attend graduate school after their program, and (IV) whether the student assisted a professor with their research. The coefficients from Specification II are the marginal effects from a probit model between the dropout (0/1) variable and the listed covariates. Faculty controls include reservation category status, professor rank, experience, highest degree, elite college, and gender. All models are run for the sample with random assignment (12 colleges), where each observation is a student-test pair (with multiple observations for students who took both physics and math baseline and endline tests). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

of planning on going to graduate school or expectation of graduating with a degree at the end of year 4. Although we find clear evidence of lower grades and test scores among reservation category students there is no evidence that reservation category students have higher dropout rates, lower expected graduation rates, and are less likely to plan to go to graduate school.

7 Teacher-Like-Me Interactions and Do Reservation Category Faculty Struggle Teaching General Category Students?

The main regressions indicate that reservation category faculty provide higher quality instruction than general category faculty, but is there heterogeneity in which students benefit the most from taking classes with reservation category faculty? For reducing inequality concerns we are interested in testing whether reservation category students do better with reservation category faculty. These faculty might serve as role models, decrease the likelihood of "stereotype threats" and discrimination against minority students, increase exposure to instructors with similar cultures and languages, and contribute to a sense of belonging at the college and major (Bettinger & Long, 2005; Dee, 2005; Fairlie, Hoffmann, & Oreopoulos, 2014). Students can infer caste levels from the surnames of faculty. We also explore whether general category students perform worse in classes taught by reservation category faculty, potentially due to factors such as resentment towards quotas, caste discrimination, and providing less effort in classrooms taught by those faculty.

We test these two hypotheses using Equation 4.2 and report estimates in Table 7.1. The main reservation category faculty coefficient captures the effect for general category students. The reservation category student variable is subsumed by the student fixed effect λ_i. Note that unlike previous studies, we can identify the absolute effect on general category students because we have random assignment to classrooms. For example, in examining racial interactions in community colleges, Fairlie, Hoffmann, and Oreopoulos (2014) focus on relative effects instead of identifying direct effects of minority faculty on non-minority students. The focus in their study is on the minority student-minority faculty interaction. Randomization allows us to directly estimate the effect on general category students. We find that general category students do slightly better in classrooms taught by reservation category faculty than in classrooms taught by general category faculty. Having a reservation category faculty increases grades by 1.5 percentiles for general category students. The estimated effect is robust to the inclusion of various faculty characteristics.

Table 7.1: Regressions for Student Course Grades Measuring Quality of Instruction, Reservation Category Faculty Interacted with Reservation Category Students

	I	II	III	IV
Res. Cat. Faculty	1.59**	1.68**	1.48**	1.49**
	(0.65)	(0.65)	(0.65)	(0.64)
Res. Cat. Faculty x Res. Cat. Student	-0.29	-0.29	-0.27	-0.29
	(0.66)	(0.66)	(0.66)	(0.66)
Associate professor		0.56	1.24	1.26
		(0.75)	(0.83)	(0.82)
Professor		1.47	2.96**	3.17**
		(0.93)	(1.36)	(1.32)
Experience in years		-0.02	-0.02	-0.01
		(0.05)	(0.05)	(0.05)
Highest degree PhD			-2.36**	-2.53**
			(1.19)	(1.17)
Highest degree PhD in progress			-0.75	-0.95
			(0.80)	(0.82)
Degree from elite college			0.37	0.30
			(0.59)	(0.59)
Female				1.09*
				(0.57)
Mean	51.19	51.19	51.19	51.19
N	37718	37667	37667	37667

Notes: The dependent variable is the student course grade measured as the percentile rank in the course (1-100 scale). Grades are provided at the course level and not at the faculty-taught section level. All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student-course. All models also control for student fixed effects and course fixed effects. Standard errors are clustered at the faculty level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Equation 4.2 also includes an interaction between reservation category faculty and students, that indicates the relative difference or extra effect for reservation category students. It is worth pointing out that reservation category students do not do as well general category students in these courses, averaging a statistically significant difference of between 4.5 to 5.5 percentile points, as indicated in Table 6.2 and Table 6.4. We find no evidence of any positive or negative differential effect of reservation category faculty on the course grade of reservation category students, relative to general category students[34].

We further build on the identification provided by random assignment of students to classes in two ways. First, we estimate a set of regressions that includes student fixed effects to control for unobservable student characteristics and make the comparison between reservation and general category faculty to teaching the same students. Second, in estimating "teacher-like-me" interactions we use regression models that include classroom (i.e. specific professor taught sections of

[34]The results are not sensitive to the removal of student fixed effects or controls.

course offerings) fixed effects which use variation between reservation and general category students when assigned to the same classroom-faculty for identification. Classroom fixed effects, which are constructed uniquely for each college-department-semester-course-classroom combination, account for classroom-specific disruptions or common shocks, differences in time of day for each class, and classroom size, among other factors. Crucially, they nest faculty fixed effects, including the reservation status of the faculty. These models combine the common difference-in-difference identification strategy used in the previous literature with our use of random assignment for identification.

Focusing on the "teacher-like-me" effects we estimate Equation 4.3 and report estimates in Table 7.2. Specification II repeats the main specification from Table 7.1 that includes course and student fixed effects and controls for the full set of faculty characteristics. Specification II includes course, student and faculty fixed effects. The inclusion of faculty fixed effects controls for additional unobserved characteristics between reservation and general category faculty that might affect the performance of all students that they teach. The reservation category student–reservation category faculty interaction captures the relative performance of reservation category students compared with general category students with the same faculty. The reservation status interaction (i.e. "teacher-like-me") coefficient does not change with the inclusion of these faculty fixed effects.

Table 7.2: Regressions for Student Course Grades Measuring Teacher-Like-Me Interactions

	I	II	III
Res. Cat. Faculty	1.49**		
	(0.64)		
Res. Cat. Faculty x Res. Cat. Student	-0.29	-0.33	-0.32
	(0.66)	(0.68)	(0.69)
Associate professor	1.26		
	(0.82)		
Professor	3.17**		
	(1.32)		
Experience in years	-0.01		
	(0.05)		
Highest degree PhD	-2.53**		
	(1.17)		
Highest degree PhD in progress	-0.95		
	(0.82)		
Degree from elite college	0.30		
	(0.59)		
Female	1.09*		
	(0.57)		
Mean	51.19	51.19	51.19
N	37667	37667	37667

Notes: The dependent variable is the student course grade measured as the percentile rank in the course (1-100 scale). Grades are provided at the course level and not at the faculty-taught section level. All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student-course. Specification I includes course and student fixed effects, Specification II includes Course, student, and faculty fixed effects, Specification III includes student and classroom fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Specification III replaces faculty fixed effects with classroom fixed effects. Classroom fixed effects subsume faculty fixed effects because each classroom is only assigned one faculty member. The inclusion of classroom fixed effects controls for additional unobserved characteristics between classrooms taught by reservation and general category faculty, that might affect the performance of all students taught in those classrooms. The reservation category student-reservation category faculty interaction captures the relative performance of reservation category students compared with general category students *in the same classrooms*. Similar to Specification II, the reservation category student-faculty interaction does not change after including these fixed effects. Even forcing the comparison to the same faculty and the same classrooms, we do not find evidence of teacher-like-me effects. Reservation category faculty teach all students slightly better but do not teach general category students relatively worse or reservation category students relatively better.

7.1 Additional Student-Faculty Interaction Regressions

A potential reason behind not observing teacher-like-me effects may be within-group heterogeneity in each reservation group (SC, ST, or OBC). We attempt to address this issue in two key ways. First, we replace the reservation category student indicator with dummy variables for combined classes of affirmative action (SC/ST and the relatively more advantaged OBC's). General category students continue to serve as the reference group. Table 7.3 reports estimates of Equation 4.2 expanding the set of interactions between reservation category faculty and different groups of students. We continue to find a slight positive effect of reservation category faculty on course grades for all students, but no evidence of positive interactions for either of the two subgroups of reservation category students. Splitting reservation category students into more detailed groups does not alter our initial results regarding reservation category faculty instruction quality or interactions.

Table 7.3: Regressions for Student Course Grades Measuring Quality of Instruction, Reservation Category Faculty Interacted with Detailed Reservation Category Student Groups

	I	II	III	IV
Res. Cat. Faculty	1.60**	1.68**	1.48**	1.50**
	(0.65)	(0.66)	(0.65)	(0.64)
Res. Cat. Faculty x SC/ST student	-0.49	-0.49	-0.48	-0.47
	(1.47)	(1.47)	(1.47)	(1.47)
Res. Cat. Faculty x OBC student	-0.23	-0.23	-0.21	-0.23
	(0.59)	(0.59)	(0.59)	(0.59)
Associate professor		0.56	1.24	1.26
		(0.75)	(0.83)	(0.82)
Professor		1.47	2.97**	3.17**
		(0.93)	(1.36)	(1.32)
Experience in years		-0.02	-0.02	-0.01
		(0.05)	(0.05)	(0.05)
Highest degree PhD			-2.36**	-2.53**
			(1.19)	(1.17)
Highest degree PhD in progress			-0.75	-0.94
			(0.80)	(0.82)
Degree from elite college			0.37	0.30
			(0.59)	(0.59)
Female				1.09*
				(0.57)
Mean	51.19	51.19	51.19	51.19
N	37718	37667	37667	37667

Notes: The dependent variable is the student course grade measured as the percentile rank in the course (1-100 scale). Grades are provided at the course level and not at the faculty-taught section level. All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student-course. All models also control for student fixed effects and course fixed effects. Standard errors are clustered at faculty level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Second, we check for interaction effects between faculty and students belonging to the same reservation category group. We define a match variable which takes the value of 1 if a student-teacher pair belong to the same group among lower caste and social class groups (i.e. SC student and SC faculty, ST student and ST faculty, OBC student and OBC faculty), and 0 otherwise. Table 7.4 reports the results of a version of Equation 4.2 with this match variable. We again find a small positive main effect of being taught by reservation category faculty, and no relative gains or losses for students resulting from being matched to a faculty of the same reservation category group.

Table 7.4: Regressions for Student Course Grades Measuring Quality of Instruction, Reservation Category Faculty Interacted with Same Reservation Category Group Student

	I	II	III	IV
Student-faculty same category	-0.08	-0.07	-0.05	-0.05
	(0.54)	(0.54)	(0.54)	(0.54)
Res. Cat. Faculty	1.46**	1.54***	1.34**	1.35**
	(0.58)	(0.59)	(0.58)	(0.57)
Associate professor		0.56	1.25	1.26
		(0.75)	(0.83)	(0.82)
Professor		1.47	2.97**	3.18**
		(0.93)	(1.36)	(1.32)
Experience in years		-0.02	-0.02	-0.01
		(0.05)	(0.05)	(0.05)
Highest degree is PhD			-2.36**	-2.54**
			(1.19)	(1.17)
Highest degree is PhD in progress			-0.76	-0.95
			(0.80)	(0.82)
Degree from elite college			0.37	0.30
			(0.59)	(0.59)
Female				1.09*
				(0.57)
Mean	51.19	51.19	51.19	51.19
N	37718	37667	37667	37667

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Student-faculty same category is defined as 1 if a student and their faculty are either both SC, both ST, both OBC, or both 'Other', and is defined as 0 otherwise. The dependent variable is the student course grade measured as the percentile rank in the course (1-100 scale). Grades are provided at the course level and not at the faculty-taught section level. Standard errors are clustered at the faculty level. All models are run on the sample of colleges with random assignment (12 colleges), where each observation is a student-course. All models also control for student fixed effects and course fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We also explore interactions between reservation category faculty and additional student characteristics. First, we examine whether reservation category faculty teach students with college-educated parents better or worse than general category faculty. We find no evidence of a differential effect for students with college-educated parents. Second, we examine whether female students perform relatively better in classrooms taught by reservation category faculty. We again find no evidence of differential reservation category faculty effects for female students.

7.2 Teacher-Like-Me Effects on Additional Educational Outcomes

We investigate whether reservation category faculty have a positive relative effect on educational outcomes for reservation category students beyond the immediate course grade. We first examine interaction effects on follow-on course grades and test scores. Reservation category faculty might inspire more interest and motivation, and improve deeper learning in engineering among reservation category students. Table 7.5 reports estimates for interaction effects for follow-on course grades, and math and physics test scores. We do not find any interaction between reservation category faculty and reservation category students.

Table 7.5: Regressions for Follow-on Course Grades and Test Scores, Reservation Category Faculty Interacted with Reservation Category Students

	I Follow-On Grade (Semester)	II Follow-On Grade (Course)	III Math Endline (z-score)	IV Physics Endline (z-score)
Res. Cat. Faculty	0.900	0.704	0.013	0.037
	(2.413)	(1.326)	(0.032)	(0.032)
Res. Cat. Student			-0.352***	-0.197**
			(0.086)	(0.097)
R.C. Faculty × R.C. Student	0.392	0.250	0.011	-0.010
	(2.640)	(1.579)	(0.017)	(0.020)
Student controls	FE	FE	Yes	Yes
Faculty controls	Yes	Yes	Yes	Yes
Mean	6.18	0.01	0.61	0.21
N	3140	1965	2156	2134

Notes: The dependent variables are (I) grade in a follow-on course based on average faculty characteristics in one prior semester, (II) grade in a follow-on course based on average faculty characteristics for *related courses* in one prior semester, (III) standardized score for math endline test, and (IV) standardized score for physics endline test. For Specifications III and IV, Res. Cat. faculty is the percentage of reservation category faculty who taught all prior courses taken by the student. The Res. Cat. variable is rescaled to capture the effect of changing the reservation category faculty percentage by 10 percentage points (e.g. from 0.50 to 0.60). Student controls include gender, age, and parents' education. Faculty controls include professor rank, experience, highest degree, elite college, and gender. All models are run for the sample with random assignment (12 colleges). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We also examine interaction effects for class attendance, dropout, graduate school plans, and working for professors on research projects. For these longer-term outcomes reservation category faculty might inspire interest, provide role models, and contribute to a sense of belonging to reservation category students. Estimates are reported in Table 7.6. We find no evidence of positive interaction effects for these educational outcomes.

Table 7.6: Regressions for Additional Educational Outcomes, Reservation Category Faculty Interacted with Reservation Category Students

	I Hours Attended	II Dropout	III Plans for Graduate School	IV Research Assistance
Res. Cat. Faculty	0.011	-0.000000	0.014	-0.009
	(0.062)	(0.000000)	(0.017)	(0.007)
Res. Cat. Student	0.355	0.000008	-0.034	0.016
	(0.247)	(0.000028)	(0.042)	(0.031)
R.C. Faculty × R.C. Student	0.066	-0.000000	0.002	0.006
	(0.055)	(0.000001)	(0.009)	(0.006)
Student controls	Yes	Yes	Yes	Yes
Faculty controls	Yes	Yes	Yes	Yes
Mean	6.18	0.01	0.61	0.21
N	3140	1965	2156	2134

Notes: The dependent variables are (I) hours per week spent attending classes, (II) whether a student dropped out, (III) whether the student aspired to attend graduate school after their program, and (IV) whether the student assisted a professor with their research. Res. Cat. faculty is the percentage of reservation category faculty who taught courses taken by the student, and is rescaled to capture the effect of changing the reservation category faculty percentage by 10 percentage points (e.g. from 0.50 to 0.60). The coefficients from Specification II are the marginal effects from a probit model between the dropout (0/1) variable and the listed covariates. Student controls include gender, age, parents' education, and math and physics baseline z-scores. Faculty controls include professor rank, experience, highest degree, elite college, and gender. All models are run for the sample with random assignment (12 colleges), where each observation is a student-test pair (with multiple observations for students who took both physics and math baseline and endline tests). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The positive effects of reservation category faculty might show up at the end of the college experiences of students. In Appendix Table E3 we report estimates of reservation category faculty and student interactions for expected graduation with degree, and graduate school plans measured at the end of year 4 for our second cohort of students. We do not find teacher-like-me effects for these longer-term outcomes. We also examine interaction effects on CS and EE test scores for the second cohort of students. We find no evidence of an interaction effect for either test score.

For all of these longer-term outcomes which are measured at the end of year 2 for the main analysis sample or the end of year 4 for the second cohort of students, we find consistent results. There is no evidence of positive or negative teacher-like-me effects on longer-term outcomes.

8 Conclusion

Although the evidence is limited, affirmative action programs are often criticized because of fears that they result in lower worker productivity (Holzer & Neumark, 2000, 2006). We explore this criticism by examining the relative productivity of workers benefiting from an aggressive affirmative action policy in a setting where constraints on hiring a diverse qualified workforce are likely to bind. In India, colleges are required to reserve approximately 50 percent of faculty hires for individuals from lower caste and social class groups to match the population. We use our nationally representative sample of 50 engineering and technology colleges in India and subset of colleges that randomly assign students to classrooms to provide novel evidence on this fundamental and understudied question about affirmative action and worker productivity. In terms of qualifications, we find that reservation category faculty have lower levels of education, lower professorial ranks and less years of work experience in academia than general category faculty. Reservation category faculty, for example, are more likely to have master's degrees and less likely to have PhDs. Yet, even with lower qualifications, we find no evidence that reservation category faculty provide lower quality instruction than general category faculty. In fact, we find that students taught by reservation category obtain slightly higher grades than students taught by general category faculty. Furthermore, even in light of potential resentment and animosity towards professors hired through reservation quotas, we find that general category students actually do slightly better (in grades) when taught by reservation category faculty. We do not find that reservation category faculty spend more time on teaching activities, and thus compensate for having lower qualifications by devoting more time to preparing and teaching classes, or advising and tutoring students.

Estimates of differential faculty effects on longer-term educational outcomes are quite consistent across several measures. For example, we find no differential effects on follow-on course grades, and math, physics, computer science and electrical engineering tests. The findings rule out that possibility of "teaching to the test" and suggest that reservation category faculty are not inferior at teaching higher-order engineering skills. Furthermore, we do not find lower instructional productivity as measured by longer-term outcomes such as course attendance, dropouts, expected graduation with a degree, graduate school plans, and research work with faculty. These findings are consistent across the two cohorts of students that we follow and their different stages in their studies captured.

Although teaching is the primary focus of the typical or representative college and instructional productivity has the added importance of affecting the future labor market outcomes of students, we also examine faculty's research productivity and administrative service. We do not find that reservation category faculty have different levels of research and service productivity than general category faculty.

Our results are especially compelling as we overcome traditional obstacles in establishing causality by leveraging the random assignment of students to classrooms as well as objective and accurate measures of teaching productivity (such as administrative grades, or standardized, third-party proctored test outcomes). We also focus on a large and important workforce which affects not only their own earnings but also the future earnings of students they teach. There are nearly a quarter of a million faculty, training close to 4.5 million students in engineering and technology colleges in India, with a growing number of graduates being hired in the United States and other countries.[35] In this context, we find that even with an affirmative action program that has large quotas and affects a highly-educated population, the popular view should not assume that these programs result in lower worker productivity.[36] Potential discrimination in the broader uncovered labor market might "push" higher-ability (e.g. more enthusiastic, articulate, motivated, etc.) reservation category workers into academia. More research using careful empirical designs such as the one used here are needed to test whether affirmative action programs lead to lower worker productivity for the targeted group in other settings. Future evidence along these lines is crucial to better inform the heated debate over affirmative action programs around the world. In India, for example, reservation policies have been protested widely even invoking riots.[37]

We also examine student performance in the context of an affirmative action program with approximately 50-percent quotas in college admissions. We find that reservation category students come from families with less parental education, and consistent with lower qualifications, have lower

[35] One in five foreign-born science and engineering degree holders working in the United States are from India (NSF, 2018).

[36] This is the view at the highest levels of higher education in India. Due to concerns over limiting the quality of instruction and research, The Central Educational Institutions (Reservation in Teachers' Cadre) Act allows for "institutions of excellence, research institutions, institutions of national and strategic importance" to be exempted from reservation requirements in the Constitution (MoE, GoI, 2019).

[37] See (BBC News, 2015; The New York Times, 2015; The New York Times, 2022). Even the specific use of lower caste and social class quotas for faculty in the elite IIT's has been debated extensively with the 2019 Ramagopal Rao Committee Report (MoHRD, GoI, 2020) arguing to abolish reservations and the Supreme Court of India in a recent case in 2022 directing IITs to follow reservation policies. Recent evidence indicates that they are generally not following quotas in hiring faculty (Paliwal, 2023).

entrance exam scores. Turning to course performance in college, we provide the first evidence on the question using random assignment of students to classrooms. In this setting, students cannot choose their faculty, courses or classrooms, and thus we capture true differences in performance between reservation category and general category students. The comparison is between students taking the same courses with randomly assigned faculty and classrooms (i.e. removing course, faculty, and classroom choice unobservables that could be correlated with both student performance and reservation status). We find that, controlling for baseline scores at the beginning of college, reservation category students obtain lower grades than general category students. They also score lower on math and physics tests that we administer at the end of the first two years of study, and score lower on major-specific electrical engineering and computer science tests that we administer at the end of the four-year program. In contrast to these findings for grades and test scores, we do not find differences in dropouts, expected graduation rates, and plans for graduate school.

Affirmative action policies often promote hiring disadvantaged and underrepresented groups with the goal of reducing inequality among the population served.[38] In education, several previous studies find large, positive "teacher-like-me" effects by which teachers from underrepresented racial groups improve the academic outcomes of similar students that they teach.[39] We do not find evidence of positive "teacher-like-me" effects of being taught by reservation category faculty on the performance of reservation category students relative to general category students. The finding is consistent across an extensive set of immediate and longer-term educational outcomes. One reason for the lack of effects is that caste discrimination might be more ingrained among students and even reservation students might associate reservation faculty as being less qualified to teach (instead of serving as a positive role model Karachiwalla (2019)). Another reason might be the considerable within-group heterogeneity of reservation groups. Finally, lower caste and social class faculty are also more prevalent at colleges because of 50 percent quotas potentially resulting in less of a role model effect. Role models might be strongest for the least represented groups among faculty. These new findings on caste interactions contribute to the scant literature which finds mixed results and focuses on K-12 education (Karachiwalla, 2019; Rawal & Kingdon, 2010).

[38] Lower-caste students are underrepresented in competitive, well- paying private jobs in STEM contributing to broader caste inequality (S. Deshpande, 2006; Upadhya, 2007).

[39] See Dee (2004, 2005); Egalite, Kisida, and Winters (2015); Ehrenberg, Goldhaber, and Brewer (1995); Gershenson, Hart, Hyman, Lindsay, and Papageorge (2022); Gershenson, Holt, and Papageorge (2016) for evidence at primary and secondary school levels, and Birdsall, Gershenson, and Zuniga (2020); Fairlie, Hoffmann, and Oreopoulos (2014); Oliver, Fairlie, Millhauser, and Roland (2021); Price (2010) for evidence at the college level.

Affirmative action programs are hotly debated and facing legal challenges around the world. These programs, especially ones with quotas, are criticized because of fears that they lead to lower qualifications and preparation, lower productivity and reverse discrimination. On the other hand, proponents argue that affirmative action programs address equity concerns in employment, fight historical discrimination, and provide role models and networks for future hires.[40] In education there is the additional argument that hiring faculty from underrepresented groups could not only provide jobs to those groups but also could help disadvantaged and underrepresented students, both reducing inequality. The empirical evidence on both sides of this important debate, however, is limited. We provide one of the first studies of worker productivity and college student performance in the context of a strict affirmative action program in hiring and admissions. More research using careful empirical designs and the comprehensive approach taken here are needed to shed light on this multi-faceted and heated debate.

[40] There is concern that caste discrimination has followed immigrants in host countries such as the United States leading to arguments for caste being added to protected group lists (NBC News, 2022; Equality Labs, 2018). The California State University (CSU) system recently added caste to its list of protected statuses (see CSU, 2023)

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Appendices

A Descriptive Statistics from NSS Micro Data

Table A1: Descriptive Statistics

		I General	II Reservation	III General vs Reservation
Mean Years of Schooling	Mean	8.0	5.2	2.99***
	SD	5.2	4.8	(0.03)
	n	39707	89223	
Proportion Graduating High School (%)	Mean	29.2	11.7	17.48***
	SD	45.5	32.2	(0.22)
	n	39709	89237	
Proportion Graduating College (%)	Mean	19.4	6.5	12.88***
	SD	39.5	24.6	(0.18)
	n	39709	89237	
Proportion with Master's or Higher (%)	Mean	5.8	1.8	4.0***
	SD	23.3	13.2	(0.11)
	n	39709	89237	
Proportion with Master's or Higher (%) (Age 25-50)	Mean	6.04	1.98	4.06***
	SD	23.8	13.9	(0.12)
	n	31706	72612	
Proportion with Regular Employment (%)	Mean	30.8	16.9	13.97***
	SD	46.2	37.4	(0.25)
	n	39709	89237	
Monthly Per Capita Consumption Expenditure (Rs)	Mean	7192.8	5554.8	1638.01***
	SD	5294.5	4040.2	(36.54)
	n	21227	60066	
Weekly Wages (Rupees)	Mean	2752.2	1399.9	1363.5***
	SD	3820.9	1731.7	(23.55)
	n	16568	40135	
Weekly Wages of College Graduates (Rupees)	Mean	5747.5	3967.7	1779.7***
	SD	5733.0	2904.9	(84.0)
	n	5445	6424	
Weekly Wages of College Graduates (Age 25-35) (Rupees)	Mean	4536.3	3159.9	1376.5***
	SD	4112.6	2382.2	(95.2)
	n	2111	2764	

Note: Estimates are calculated using microdata from the National Sample Survey Organization's 68th Round: Employment and Unemployment Survey of 2011-12, and weighted by population using NSS multipliers. Column III reports the difference between the means in Column I (general) and column II (reservation), with the standard errors reported in parentheses. Column III reports the general category-reservation category difference in means. Monthly per capita consumption expenditure is computed at the household level. Significance levels: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B Summary Statistics: Sample of Colleges with Random Assignment

Table B1: Faculty and Student Characteristics: Sample of Colleges with Random Assignment

Attribute		
	Faculty	
	Mean	SD
Reservation Category	0.40	0.49
Assistant professor	0.72	0.45
Associate professor	0.18	0.38
Professor	0.08	0.27
Experience (Years)	9.96	6.51
Highest Degree Master's	0.51	0.50
Highest Degree PhD in progress	0.15	0.36
Highest Degree PhD	0.32	0.47
Degree from Elite College	0.32	0.47
Female	0.33	0.47
N	501	501
	Students	
	Mean	SD
Reservation Category	0.54	0.50
Female	0.44	0.50
Age (years)	17.72	0.80
Father attended college	0.50	0.50
Mother attended college	0.35	0.48
N	2268	2268
Number of colleges	12	12
Number of departments	20	20

C Course Assignment by Faculty Group

Table C1: Course Assignments by Faculty Reservation Category Status

Panel A: Nationally Representative Sample		
	Reservation Category Faculty	**General Category Faculty**
Semester 1	48.4%	51.6%
Semester 2	45.0%	55.0%
Semester 3	50.4%	49.6%
Semester 4	53.3%	46.7%
N	95400	114993
Panel B: Sample with Random Assignment		
	Reservation Category Faculty	**General Category Faculty**
Semester 1	36.4%	63.6%
Semester 2	35.4%	64.6%
Semester 3	45.6%	54.4%
Semester 4	42.2%	57.8%
Introductory Courses	34.4%	65.6%
Advanced Courses	46.0%	54.0%
N	14938	23083
Panel C: Nationally Representative Sample (Second Cohort)		
	Reservation Category Faculty	**General Category Faculty**
Year 1	43.83%	56.17%
Year 2	46.0%	54.0%
Year 3	46.6%	53.4%
Year 4	44.6%	55.4%
N	172686	231589

Notes: Panel A reports the percentage of all courses (classrooms) in each semester of the first two years of the program, assigned to reservation category and general category faculty for the full sample of 50 colleges. Panel A reports the percentage of all courses (classrooms) in each semester of the first two years of the program, assigned to reservation category and general category faculty for the sample of colleges with random assignment (12 colleges), for the first cohort of students. Panel C reports the percentage of all courses (classrooms) in each semester of all four years of the program, assigned to reservation category and general category faculty for the full sample of 50 colleges, for the second cohort of students. The unit of analysis is a student-course.

D Robustness Checks

D.1 Main Results without Student Fixed Effects

Table D1: Regressions for Student Course Grades Measuring Quality of Instruction, Reservation vs. General Category Faculty: Without Student Fixed Effects

	I	II	III
Res. Cat. Faculty	1.22*	1.20*	1.34**
	(0.64)	(0.64)	(0.56)
Associate professor	1.02	1.07	1.27
	(0.88)	(0.89)	(0.82)
Professor	4.03***	4.04***	3.18**
	(1.38)	(1.46)	(1.32)
Experience in years	0.00	0.02	-0.01
	(0.06)	(0.06)	(0.05)
Highest degree PhD	-2.94**	-3.29***	-2.55**
	(1.18)	(1.21)	(1.17)
Highest degree PhD in progress	-0.31	-0.52	-0.94
	(1.01)	(1.03)	(0.82)
Degree from elite college	0.06	0.10	0.31
	(0.72)	(0.71)	(0.59)
Female	1.40**	1.47**	1.09*
	(0.63)	(0.63)	(0.57)
Student characteristics	None	Main Controls	Fixed Effects
N	37716	37716	37716

Notes: The dependent variable is the student course grade measured as the percentile rank in the course (1-100 scale). Grades are provided at the course level and not at the faculty-taught section level. Column (I) reports the results without using any student-level controls or fixed effects, column (II) uses student controls (their reservation status, age, gender, and parents' education), and column (III) includes student fixed effects, replicating the specification of Table 5.4. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

D.2 Inverse-Weighted Observations by Classroom Size

Table D2: Regressions for Student Course Grades Measuring Quality of Instruction Weighting Each Classroom the Same, Reservation vs. General Category Faculty

	I	II	III	IV
Res. Cat. Faculty	1.52	1.69*	1.65*	1.73*
	(0.93)	(0.93)	(0.92)	(0.91)
Associate professor		-0.87	-0.67	-0.72
		(1.03)	(1.15)	(1.14)
Professor		2.03	2.49	2.66
		(1.73)	(1.95)	(1.93)
Experience in years		0.01	0.01	0.01
		(0.07)	(0.07)	(0.07)
Highest degree is PhD			-0.80	-1.05
			(1.52)	(1.52)
Highest degree is PhD in progress			-0.16	-0.31
			(1.20)	(1.20)
Degree college elite			0.21	0.11
			(1.10)	(1.10)
Female				1.41
				(0.88)
N	37767	37716	37716	37716

Notes: The dependent variable is the student course grade measured as the percentile rank in the course (1-100 scale). Grades are provided at the course level and not at the faculty-taught section level. Reciprocal of classroom sizes are used as regression weights. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

E Characteristics and Outcome Regressions for Second Cohort of Students

Table E1: Faculty Differences and Balance Checks for the Sample of Colleges with Random Assignment (Second Cohort of Students)

	Panel A: Faculty			
Faculty characteristics	**Mean**	**SD**	**Res.-Gen. Faculty**	**SE**
Reservation Category	0.38	0.48	1.000	
Assistant professor	0.72	0.45	0.095**	0.048
Associate professor	0.16	0.37	-0.044	0.040
Professor	0.08	0.27	-0.034	0.034
Experience in years	10.05	6.84	-1.035	0.684
Highest degree is Masters	0.54	0.50	0.005	0.053
Highest degree is PhD	0.25	0.43	-0.054	0.042
Highest degree is PhD in progress	0.19	0.40	0.032	0.048
Degree from elite college	0.30	0.46	0.083*	0.045
Female	0.33	0.47	-0.036	0.053
	Panel B: Students			
Student characteristics	**Mean**	**SD**	**Res.-Gen. Faculty**	**SE**
Reservation Category	0.49	0.50	-0.003	0.009
Female	0.45	0.50	-0.004	0.008
Age	19.76	0.99	0.011	0.013
Father attended college	0.56	0.50	0.003	0.007
Mother attended college	0.39	0.49	-0.002	0.006
Baseline math score	0.00	1.00	-0.007	0.019
Baseline physics score	0.00	1.00	-0.014	0.015
JEE Main score	79.74	38.53	-0.662	0.587
Took JEE Main	0.66	0.48	0.001	0.009

Notes: Estimates are calculated using the second cohort of students. Means and standard deviations for general category faculty characteristics are reported in Panel A. Means and standard deviations for all sampled students are reported in Panel B. The sample of colleges with random assignment (12 colleges) is used, and the unit of analysis is a student-course. The data capture 2289 students and 650 faculty. The reservation vs general category differences control for course fixed effects, and corresponding standard errors are clustered at the faculty level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table E2: Regressions for Additional Educational Outcomes by Student Reservation Category Status (Second Cohort of Students)

	I EE Test (Year 4)	II CS Test (Year 4)	III Expected Graduation (Year 4)	IV Plans for Graduate School (Year 4)
Res. Cat. Student	-0.185***	-0.375***	-0.00017	-0.004
	(0.057)	(0.081)	(0.00021)	(0.023)
Female	-0.151**	-0.085	0.00046*	-0.041
	(0.066)	(0.083)	(0.00024)	(0.027)
Age	-0.064**	-0.030	-0.00009	0.019*
	(0.026)	(0.032)	(0.00006)	(0.011)
Father attended college	0.064	-0.002	-0.00048**	0.030
	(0.070)	(0.086)	(0.00024)	(0.027)
Mother attended college	0.033	0.128	0.00044**	0.074***
	(0.070)	(0.088)	(0.00022)	(0.027)
Faculty controls	Yes	Yes	Yes	Yes
Mean	0.00	-0.03	0.99	0.51
N	1060	510	2247	2083

Notes: The dependent variables are measured at the end of year 4 and are (I) standardized test score for the electrical engineering (EE) test, (II) standardized test score for the computer science (CS) test, (III) whether the student expected to graduate, and (IV) whether the student aspired for graduate school after completing their program. Faculty controls include reservation category status, professor rank, experience, highest degree, elite college, and gender. The coefficients from Specification III are the marginal effects from a probit model between the expected graduation (0/1) variable and the listed covariates. All models are run on the second cohort of students for the sample with random assignment (12 colleges), where each observation is a student. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table E3: Regressions for Additional Educational Outcomes, Reservation Category Faculty Interacted with Reservation Category Students (Second cohort of students)

	I EE test (Year 4)	II CS test (Year 4)	III Expected Graduation (Year 4)	IV Plans for Graduate School (Year 4)
Res. Cat. Faculty	-0.041	-0.001	-0.00008	0.010
	(0.033)	(0.049)	(0.00011)	(0.013)
Res. Cat. Student	-0.300**	-0.120	-0.00028	0.030
	(0.136)	(0.137)	(0.00047)	(0.051)
R.C. Faculty × R.C. Student	0.025	-0.051	0.00002	-0.008
	(0.026)	(0.032)	(0.00008)	(0.011)
Faculty controls	Yes	Yes	Yes	Yes
Student controls	Yes	Yes	Yes	Yes
Mean	0.00	-0.03	0.99	0.51
N	1060	510	2247	2083

Notes: The dependent variables are measured at the end of year 4 and are (I) standardized test score for the electrical engineering (EE) test, (II) standardized test score for the computer science (CS) test, (III) whether the student expected to graduate, and (IV) whether the student aspired for graduate school after completing their program. Res. Cat. faculty is the percentage of reservation category faculty who taught courses taken by the student, and is rescaled to capture the effect of changing the reservation category faculty percentage by 10 percentage points (e.g. from 0.50 to 0.60). Student controls include gender, age, and parents' education. Faculty controls include reservation category status, professor rank, experience, highest degree, elite college, and gender. The coefficients from Specification III are the marginal effects from a probit model between the expected graduation (0/1) variable and the listed covariates. All models are run on the second cohort of students for the sample with random assignment (12 colleges), where each observation is a student. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

F Extra Measures of Research

Table F1: Regressions for Number of SCI, EI or SSCI Publications per Year, Reservation Category vs. General Category Faculty using the National Sample

	I	II	III	IV
Res. Cat. Faculty	-0.0541	0.0036	0.0037	-0.0031
	(0.0427)	(0.0417)	(0.0413)	(0.0407)
Associate professor		0.2106***	0.1301*	0.1336**
		(0.0744)	(0.0681)	(0.0667)
Professor		0.9432***	0.7717***	0.7622***
		(0.2142)	(0.2141)	(0.2134)
Experience in years		0.0106**	0.0081	0.0078
		(0.0053)	(0.0054)	(0.0053)
Highest degree PhD			0.2517***	0.2554***
			(0.0760)	(0.0743)
Highest degree PhD in progress			0.0084	0.0061
			(0.0368)	(0.0368)
Degree from elite college			0.0874*	0.0844
			(0.0527)	(0.0522)
Female				-0.0648**
				(0.0294)
Mean	0.53	0.53	0.53	0.53
N	2691	2685	2680	2679

The dependent variables are the number of articles authored by a faculty that were published in SCI (Science Citation Index), SSCI (Social Sciences Citation Index), and EI (Engineering Index) listed journals. The regressions use department-level sampling weights, and are run at the faculty level for the national sample (50 colleges). All specifications include college and department fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F2: Regressions for Government Funding Received, Reservation vs. General Category Faculty using the National Sample

	I	II	III	IV
Res. Cat. Faculty	-0.0059	0.0026	0.0018	0.0010
	(0.0090)	(0.0085)	(0.0086)	(0.0084)
Associate professor		0.0253	0.0164	0.0168
		(0.0159)	(0.0172)	(0.0171)
Professor		0.1536***	0.1353***	0.1341***
		(0.0352)	(0.0358)	(0.0358)
Experience in years		0.0010	0.0011	0.0010
		(0.0009)	(0.0009)	(0.0009)
Highest degree PhD			0.0212	0.0217
			(0.0169)	(0.0168)
Highest degree PhD in progress			-0.0184**	-0.0186**
			(0.0093)	(0.0093)
Degree from elite college			-0.0120	-0.0124
			(0.0117)	(0.0117)
Female				-0.0077
				(0.0080)
Mean	0.097	0.097	0.097	0.097
N	2691	2685	2680	2679

The dependent variable is government research funding received at college (0/1). The regressions use department-level sampling weights, and are run at the faculty level for the national sample (50 colleges). All specifications include college and department fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F3: Regressions for Private Funding Received, Reservation vs. General Category Faculty using the National Sample

	I	II	III	IV
Res. Cat. Faculty	-0.0021	-0.0006	-0.0003	-0.0024
	(0.0074)	(0.0077)	(0.0077)	(0.0078)
Associate professor		-0.0039	-0.0131	-0.0121
		(0.0100)	(0.0112)	(0.0112)
Professor		0.0216	0.0036	0.0006
		(0.0211)	(0.0222)	(0.0222)
Experience in years		0.0007	0.0005	0.0004
		(0.0007)	(0.0007)	(0.0007)
Highest degree PhD			0.0323**	0.0334**
			(0.0143)	(0.0143)
Highest degree PhD in progress			0.0128	0.0121
			(0.0086)	(0.0086)
Degree from elite college			-0.0105*	-0.0114*
			(0.0062)	(0.0062)
Female				-0.0200***
				(0.0062)
Mean	0.029	0.029	0.029	0.029
N	2691	2685	2680	2679

The dependent variable is private research funding received at college (0/1). The regressions use department-level sampling weights, and are run at the faculty level for the national sample (50 colleges). All specifications include college and department fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F4: Regressions for Research, Funding, and Administration for the Sample of Colleges with Random Assignment, Reservation vs. General Category Faculty (Student-Course Level)

	I Publications	II International Publications	III SCI/EI/SSCI Publications	IV Funding Received	V Administrative Position
Res. Cat. Faculty	-0.37	-0.29**	-0.10	-0.03	0.03
	(0.27)	(0.14)	(0.09)	(0.02)	(0.05)
Associate professor	1.11***	0.92***	0.33**	0.07	0.01
	(0.37)	(0.20)	(0.16)	(0.07)	(0.07)
Professor	1.80***	1.16***	0.72**	-0.01	0.02
	(0.69)	(0.45)	(0.31)	(0.07)	(0.11)
Experience in years	-0.06**	-0.02*	-0.02*	0.00	0.02***
	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)
Highest degree PhD	2.37***	0.92***	0.66**	0.23***	0.19*
	(0.78)	(0.29)	(0.26)	(0.07)	(0.11)
Highest degree PhD in progress	1.06***	0.53***	0.12	0.01	-0.11*
	(0.39)	(0.17)	(0.11)	(0.03)	(0.06)
Degree from elite college	0.16	0.00	0.00	-0.09***	0.00
	(0.32)	(0.18)	(0.12)	(0.04)	(0.06)
Female	-0.24	-0.20	-0.07	0.09***	0.06
	(0.24)	(0.12)	(0.09)	(0.03)	(0.05)
N	37970	37970	37970	37970	37970

Notes: Dependent variables refer to annual publications (I), annual international publications (II), annual international SCI/EI/SSCI publications (III), funding received (IV), and administrative position held (V). The regressions are run at the student-course level for the sample of colleges with random assignment (12 colleges). All specifications include student fixed effects and course fixed effects. Standard errors are clustered at the faculty level. Significance levels: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.