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 over lower worker productivity. Engineering colleges in India are required to reserve 50 percent of faculty hires from lower caste groups with some colleges randomly assigning students to classrooms. We find that reservation category faculty have less experience and lower credentials than general category faculty but we do not detect meaningful differences in instructional, research and administrative productivity. In fact, we find that for immediate effects on course grades, students taught by reservation category faculty perform slightly better. Examining heterogeneity among students, we cannot reject the hypothesis of null "teacher-like-me" effects.

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

JEL Codes: J78, J15, I24, I23

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

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highly educated workforce (for which they have been criticized).[1] More recently, all DEI programs have come under scrutiny by the federal government. 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]

Opponents of affirmative action programs often argue that workers hired through such programs, especially those that invoke quotas, have lower qualifications and are accordingly less productive (i.e. there is an equity vs efficiency tradeoff). 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. 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 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; Dee, 2005; Fairlie, Hoffmann, & Oreopoulos, 2014). The evidence on this important question using objective measures of productivity

[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 roughly half of the positions in political bodies, various forms of employment and promotion, as well as education admissions, are reserved for disadvantaged caste and social class groups (Article 15, CoI, 1948).

and productivity differences estimated without bias is especially limited.

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 mandated upon employers. Specifically, we examine the reservation policy in colleges in India, which sets strict quotas on hiring around half of faculty and admitting around half of students from disadvantaged 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 examine heterogeneity in instructional productivity along the dimension of student's reservation status which is related to large differences in educational attainment. 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 these faculty who are hired through 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 basic academic skills (i.e. math and physics knowledge), electrical engineering (EE) and computer science (CS), dropouts, expected graduation with a degree and additional longer-term student outcomes, as well as faculty research productivity such as publications, grants received, and administrative service.[3]

Estimating the effects of being taught by reservation category faculty on student performance, however, is usually fraught with issues of potential selection bias. General category students who have more animosity or believe that they cannot learn as well from reservation category faculty might avoid classes taught by those faculty. Reservation category students may sort into classes taught by reservation category faculty, especially by the students who value those interactions the most. To address these threats to identification, we analyze data from the engineering colleges that randomly assign students to faculty-taught sections within courses (hereafter "classrooms"). Random assignment of students to classes does not typically occur in higher education with only a few exceptions.[4] Another important feature in these

[3]India's official national ranking of colleges explicitly rewards the outcomes we study such as graduation, exam grades, exam pass rates, and faculty publications (Ministry of Human Resource Development, Government of India, 2024).

[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).

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 giving higher course marks. Also, 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).

We find that reservation category faculty 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 whether or not we control for various sets of faculty characteristics as controls, student fixed effects, and course fixed effects. The distributions of faculty productivity between reservation and general category faculty are similar. Furthermore, we cannot reject the null hypotheses that reservation category faculty put the same amount of time into teaching, measured along a range of dimensions, and employ the same teaching practices. Consistent with the findings for immediate effects on course grades, we do not detect meaningful differences between reservation category and general category faculty for longer-term outcomes such as follow-on course grades, standardized test scores after 2 and 4 years, course attendance, dropouts, expected graduation with a degree, and graduate school plans. We also find estimates of differences between reservation category and general category faculty in research productivity and administrative service that are small in magnitude and not statistically different from zero.

Focusing on heterogeneity in teaching productivity by student type, we do not detect meaningful "teacher-like-me" effects. There is no statistically significant difference between the performance of reservation category students taught by reservation category 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. Taken together, these findings have implications for the heated debates over affirmative action programs in many countries around the world.

Colleges in India provide an important testing ground for understanding the relative productivity of workers hired through affirmative action, in a setting where a large-scale affirmative action program for students contributes a pool of candidates who are potentially equally productive, but may not have had the requisite minimum qualifications required to apply for such jobs had it not been for affirmative action in student admissions. India is now the largest country in the world, and has the most aggressive affirmative action program in higher education in the world.[5] 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).[6] On the other hand, there is considerable discrimination in the private labor market against workers of disadvantaged 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 disadvantaged caste and social class groups (Madheswaran & Attewell, 2007; Shukla, 2022; Upadhya, 2007).[7] 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 all engineering degrees awarded each year globally (NSF, 2018).[8] Finally, focusing on engineering and technology colleges is important because of the role that these colleges play in providing opportunities for upward economic and social mobility for lower-caste and lower social class groups. In this regard, our research speaks to the broader question of whether faculty that a college is mandated to hire through a caste-based quota are comparably as effective as faculty chosen by the college unrestrictedly, given a setting in which there is also a large-scale affirmative action program in educating and providing credentials for those faculty.

Our paper contributes to two major strands of the literature. First, we contribute to the literature on

[5]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 U.S. higher-education system, the California Community College system, 51 percent of enrolled students are from underrepresented groups but only 21 percent of tenured faculty are from these groups (Ed Source, 2020).

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

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

[8]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).

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 extremely limited (Holzer & Neumark, 2006).[9] We provide new evidence on affirmative action workers having similar, or in the case of immediate grades slightly higher, productivity in a key dimension of their jobs. Our analysis provides novel findings on affirmative action and faculty positions in general, and new evidence focusing on reservations and worker productivity in India. Previous work on affirmative action and worker productivity has focused on railway workers (A. Deshpande & Weisskopf, 2014) and on bureaucratic performance of Indian Administrative Service (IAS) employees (Bhavnani & Lee, 2021). The literature on the effects of the Indian affirmative action policy in education is surprisingly thin. Research in India has primarily focused instead on reservation policies for student admissions and outcomes and future labor market outcomes (Bagde, Epple, & Taylor, 2016; Bertrand, Hanna, & Mullainathan, 2010; Cassan, 2019; Shukla, 2022). Our paper is the first to take advantage of the random assignment of students to classrooms to alleviate concerns over selection bias in estimating faculty productivity on immediate and long-term student outcomes. In addition to our findings on student outcomes, we also provide evidence on whether reservation category and general category faculty differ in their research productivity and administrative service across a nationally representative sample of colleges.

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, 2021) and college level (Birdsall, Gershenson, & Zuniga, 2020; Fairlie, Hoffmann, & Oreopoulos, 2014; Oliver, Fairlie, Millhauser, & Roland, 2021; Price, 2010).[10] 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 or race and affirmative action groups, in the context of post-secondary education. Random assignment to classrooms also allows

[9] 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.

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

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.[11]

2 Caste System and Reservation Policy Setting

The Indian caste system has existed since 1500 BC. There are four major hierarchical classes, or *varnas*, with each class consisting of potentially thousands of castes, or *jatis*, with their own 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 has also been an indicator of occupational groups, with each caste historically mapped to an occupational guild. After independence from British colonial rule in 1947, the Indian government established an affirmative action system, called "reservations," that sought to increase the representation of historically disadvantaged castes in public education, central and state government positions, and local and national politics through strict quotas.[12] 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).

Official, nationally-representative government reports showing caste disparities in educational and economic outcomes are limited. To fill this void, we analyzed microdata from the nationally representative Employment and Unemployment Survey (NSSO, 2013), conducted by India's National Sample Survey (NSS) Organisation 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 document large differences between the general category and reservation group population, with the general category on average having spent over 2 additional years in school, and high school and college graduation rates for the general category being 15.1 percentage points and 11.2 percentage points higher respectively. Employment in regular jobs is much lower among groups qualifying for reservation policies, with the general category population having a 4.2 percentage point 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 35 years. Monthly per capita con-

[11] 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).

[12] See Weisskopf (2004) for a comparison with affirmative action systems in the US.

sumption expenditure for reservation category households is also significantly lower than general category households.

3 Data and Classroom Assignment

3.1 Nationally Representative Sample

To study faculty productivity and faculty-student interactions we collected survey 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 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.

The sampling procedure consisted of three main steps taking place from October to December 2017 and January to March 2019. 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 technology college enrollment in India.[13] Furthermore, these departments comprise roughly one out of every four undergraduate (bachelor's degree) majors in STEM in India. In the second step, we randomly selected colleges that had these CS and EE programs from elite and non-elite college strata.[14] The national sample of colleges thus represent the range of elite and non-elite institutions in India.[15] In the third step, we sampled all first-year students from one randomly sampled CS department and one EE department from each college. 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 cate-

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

[14] 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 developed by the Ministry of Human Resource Development, Government of India.

[15] Most engineering colleges in India have not traditionally placed an emphasis on research productivity among their faculty and have levels of resources and support that are more similar to U.S. state colleges or even community colleges than research universities. The primary basis for promotions and evaluations is experience and degree qualifications (AICTE, 2019a). Teaching assistants are present but not used extensively other than at elite engineering colleges. Faculty mostly run tutorials or labs on their own. To substitute for the lack of institutional support in most colleges, peer networks and student clubs help students (e.g. more junior students may be informally tutored by more senior students).

gory 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 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 and Student Characteristics

We report new findings on faculty characteristics and qualifications from our nationally representative sample of 50 engineering and technology colleges (Table 3.1). Consistent with reservation policies, 50 percent of faculty in our nationally representative sample belong to the reservation category.[16] 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. Forty-two percent of faculty are female.

[16] Engineering colleges in India typically advertise vacancies for permanent faculty positions separately by each reservation category, in line with hiring guidelines from the AICTE (AICTE, 2019a, pg30). There is virtually no reported public information on whether quotas bind or even faculty characteristics across colleges. We find that the majority of colleges (in the two departments) that we surveyed have reservation category percentages that fall within a band of roughly 15 percentage points on either side of 50 percent. Colleges not complying with reservation policies could face legal challenges, administrative actions, and political and public pressure often from the media, and student and faculty unions. Thus, noncompliance is often enforced through a combination of roster approval, monitoring by government authorities, legal recourse through courts, financial penalties, political oversight, and public scrutiny.

Table 3.1: Faculty and Student Characteristics in Engineering 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
	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

Note: Estimates use department-level sampling weights defined across the full national sample of surveyed colleges, which includes 50 colleges and 100 departments. The sample sizes of faculty and students are 2,710 and 20,239, respectively.

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 and 41 percent 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.

3.3 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. See Fairlie, Khanna, Loyalka, and Sachdeva (2025a) for more details. These departments indicated they used a formal, computerized procedure for the random assignment. 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 specific compositions of faculty and classmates. 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 enrollment for that semester.

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. Grades are not standardized across the colleges with some colleges providing letter grades and others providing grades on a scale of 1-100. We standardize across courses and colleges by creating a ranking of all students within a course.

Appendix Table B1 reports faculty qualifications and student characteristics for our sample of 12 colleges that randomly assign students to classrooms. We find that 40 percent of faculty belong to the reservation category in our sample with random assignment.[17] Most professors are at the assistant professor rank (72%), and fewer are at the associate (18%) and full (8%) professor ranks. Roughly one-third of faculty earned their degree from an elite college and one-third are female. The 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. For students, we find that 54 percent of students belong to the reservation category and 44 percent are female. Overall, the student characteristics for the 12-college sample are similar to those for the national sample.

Our main analysis sample follows one cohort of students over their first two years of coursework. In addition to course grades, we collected information on several longer-term outcomes such as scores from standardized and proctored academic skills tests that cover basic math and physics (which are rare in higher education), class attendance, dropouts, plans to go to graduate school, and research work with professors. 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 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.

[17]While colleges are mandated to reserve 50% of faculty positions for disadvantaged groups, many colleges may have positions that remain vacant at the end of the hiring cycle due to a shortage of qualified candidates (The Hindu, 2021). This, along with the difficulty of achieving exact ratios in small departments, could lead to the ratio of reserved category faculty deviating from 50%.

4 Econometric Methods

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. The base regression for student course grades and follow-on course 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 for reservation category faculty and 0 for general category faculty), T_f is a vector of teacher characteristics for faculty f, λ_k are course fixed effects (i.e. college-department-semester offerings of courses), λ_i are student fixed effects, and ϵ_{ikcf} is the error term. Classrooms are taught by only one faculty and are within courses. We include student fixed effects to capture observable and unobserved student characteristics such as the reservation status of the student, ability, aptitudes, and socioeconomic backgrounds.

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 difference in teaching performance on account of those policies. This specification is of most interest for evaluating the relative instructional productivity of faculty hired through reservation policies directly taking into account the effects of any differences in qualifications. Another goal is to better understand differences in quality of instruction by reservation status, conditioning on faculty qualifications.[18] Conditioning on faculty qualifications provides evidence on whether any observed productivity differential between the two groups of faculty is capturing reservation status per se, or another related characteristic.

We next examine heterogeneity in instructional productivity by student type. To test whether reservation category students perform better when taught by reservation category faculty than with general category faculty (i.e. test for "teacher-like-me" effects), 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. We start with the following model:

[18] We do not have an underlying a priori ranking of faculty to determine if reservation category faculty would have been hired in the general category pool. Marginal reservation caste faculty (those hired because of the quota) might be less productive, and inframarginal reservation caste faculty might be more productive than general category faculty but we can only measure the weighted average productivity of the two, and not necessarily the productivity of only quota hires.

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

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.

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. We also estimate a model with classroom fixed effects λ_c, which in turn subsume both the course fixed effect λ_k and the faculty fixed effect λ_f. 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 which might imply that they are 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. Table 5.1 reports average faculty qualifications (educational degrees, professorial rank, and years of experience) by reservation status and the difference between the two. 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). 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.[19]

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 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

[19] 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.

for general category and reservation category workers using NSS microdata.[20] The results, presented in Table 5.2 indicate a negative and significant wage gap for workers from the disadvantaged 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). Discrimination in the private sector might lead high-ability (along unobservable traits) reservation category workers to faculty positions. Thus, lower measurable faculty qualifications among reservation category faculty do not necessarily imply that they are less qualified to teach students.

Table 5.2: Returns to Education by Reservation Status

	(I)	(II)	(III)	(IV)	(V)	(VI)
	Dependent Variable: ln(Weekly Wages in Rupees)					
College degree	1.291***	1.179***	0.677***	0.678***	0.330***	0.686***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)
Res. Category	-0.254***	-0.125***	-0.045**	-0.027	-0.158***	-0.096**
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
College degree × Res. Category	-0.073	-0.160***	-0.170***	-0.180***	0.030	-0.168***
	(0.05)	(0.04)	(0.03)	(0.03)	(0.04)	(0.06)
Age		0.046***	0.039***	0.026**	0.070***	0.062***
		(0.00)	(0.00)	(0.01)	(0.02)	(0.02)
Age^2		-0.000***	-0.000***	-0.000	-0.001***	-0.001***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female		-0.536***	-0.492***	-0.473***	-0.459***	-0.376***
		(0.02)	(0.01)	(0.02)	(0.03)	(0.04)
Urban		0.426***	0.197***	0.190***	0.282***	0.232***
		(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	59027	59027	58650	42657	18387	5935

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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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. To answer this question there are concerns about

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

selection bias. Reservation category faculty might be assigned to different courses, and have different students choose their classes. 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.

Before turning to the regression results, we present differences in faculty characteristics by reservation status (Table 5.3). 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. 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	0.69	0.46	0.055	0.061
Associate professor	0.20	0.40	0.018	0.043
Professor	0.09	0.29	-0.071	0.043
Experience in years	10.50	6.35	-1.391*	0.793
Highest degree is Masters	0.54	0.50	0.147**	0.074
Highest degree is PhD	0.26	0.44	-0.133***	0.041
Highest degree is PhD in progress	0.18	0.38	-0.023	0.068
Degree from elite college	0.28	0.45	-0.109*	0.063
Female	0.34	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 academic skills score	0.00	1.00	-0.004	0.020
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 and all students are reported in Panels A and B, respectively. 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 the random assignment of student classrooms to faculty by reservation status. 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 do not find statistical differences in student characteristics 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 in magnitude. Importantly, we have balance on the JEE scores and the baseline academic skills tests that we administered. 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).

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. As shown in Table 5.3, reservation category faculty are 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

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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

coefficient estimate on reservation category faculty does not noticeably change.

The estimates are robust to several alternatives (see Fairlie et al. (2025a)). First, 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 (Appendix Table G1). Second, 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). Third, we find similar estimates upon restricting the analysis to those courses that always have multiple classrooms. Fourth, we estimate the set of regressions including separate OBC and SC/ST indicators and find positive and statistically significant coefficients for both groups (Appendix Table G3). Finally, we estimate regressions in which student-course observations are weighted to equalize the influence of all classroom sizes (Appendix Table G2).

5.3 Distribution of Faculty Productivity

The estimation results reported in Table 5.4 test for average differences between reservation category and general category faculty. To explore heterogeneity in faculty productivity, we also construct value-added measures for each (eligible) teacher in the sample, similar in spirit to Carrell and West (2010) and Figlio, Schapiro, and Soter (2015). We construct two measures; the first uses students' prior semester GPA as a baseline measure and controls for a variety of demographic and predetermined factors. The second measure uses the score from the baseline academic skills test that students took before they started the program as the baseline measure, and controlling for other demographic and pre-determined characteristics.[21] Appendix Figure E1 and Figure E2 compare the distributions of faculty fixed effects estimates for both reservation category and general category faculty.[22] On examining the cumulative distributions of value-added measures (Appendix Figure E2), at no point in the distribution do we see reservation category faculty performing significantly worse than general category faculty.

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.

5.4 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? 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 such as weekly hours on advising students, course-related work, lesson planning, teaching class, and tutoring students (see Appendix Table F1 and Fairlie, Khanna, Loyalka, and Sachdeva (2025b)). The estimates for faculty differences in hours spent on teaching-related activities are small in magnitude and not statistically different from zero. The finding for weekly hours spent teaching classes 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 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

[21] For the first measure, student course grades are regressed on past-semester GPA, pre-determined student characteristics, teacher fixed effects, and course fixed effects. For the second measure, student course grades are regressed on the academic skills baseline test score for the first semester, past-semester GPA's for semesters 2-4, pre-determined student characteristics, teacher fixed effects, and course fixed effects. Empirical Bayesian shrinkage estimates of teacher fixed effects are reported. Since we only have course-grade data on one cohort of students, we are unable to construct leave-out value added measures, as is standard in the literature.

[22] The standard deviation of z-score course grades is 0.07 for both measures. Faculty fixed effects for course grades as estimated in Table 5.4 have a standard deviation of 23.2.

a test of whether there are potential differences in the types of teaching practices used in 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.[23] The estimates are small in magnitude and statistically insignificant for each teaching practice (see Appendix Table F2 and Fairlie et al. (2025b)). 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. See Fairlie et al. (2025a) for further discussion.

5.5 Additional Measures of Teaching Productivity

We explore several additional measures of teaching productivity by faculty.[24] Productivity might differ between reservation category and general category faculty, in a way that is not captured by effects on immediate course grades. Estimates of effects on course grades, for example, might capture differences in "teaching to the test" instead of learning outcomes that extend beyond that course (Carrell & West, 2010). An effective instructor of a course might have positive spillovers on how students do in subsequent courses in the same subject or in general. Thus, we examine faculty effects on follow-on courses using two measures. First, we regress student course grades on average faculty characteristics from one prior semester. Second, we measure the reservation category variable as the proportion of reservation category faculty who taught a student over all precursor courses they took in the previous semester 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 5.5 reports estimates. We do not detect meaningful differences between reservation category and general category faculty effects on follow-on course grades.

Table 5.5 also reports faculty effects for academic skills tests which further capture whether students increase general engineering-related knowledge. We administered and proctored our own test for academic skills (i.e. math and physics knowledge) at the end of the first two years for half of the students. Baseline test scores are included as additional controls, and the reservation category faculty variable is scaled to capture a 10 percentage point change in reservation category faculty taught courses taken over the first two years. We do not detect meaningful differences between reservation category faculty and general category faculty in the academic skills test scores. All of the estimates reported in Table 5.5 are similar after controlling for faculty characteristics (see Fairlie et al. (2025b)).

[23] Studies argue 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).

[24] We view instructional productivity through course grades (as these are based on higher-level entity exams) as the primary measure of productivity, and do not adjust standard errors for multiple hypothesis testing. The confidence intervals would be wider if we did.

Table 5.5: 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 Academic Skills
Res. Cat. Faculty	0.484 (1.660)	0.934 (0.787)	0.010 (0.010)
Student controls	FE	FE	Yes
Mean	51.84	51.67	-0.006
N	23218	11743	2181

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, and (III) standardized scores for an academic skills test administered at the end of the first two years. For Specification III, Res. Cat. faculty is the percentage of reservation category faculty taught courses taken, and is rescaled to capture a 10 percentage point change (e.g. from 0.50 to 0.60). Student controls include reservation category status, gender, age, and parents' education. The random assignment college sample is used. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We examine two additional measures of faculty productivity that capture course attendance and drop outs. Table 5.6 reports estimates. We measure course attendance by the average daily hours attending classes (mean=6.2). The estimate is small in magnitude and not statistically different from zero.[25] 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). No meaningful difference in effects on dropout rates is detected. We also find that no students in our sample switch majors in the first two years.

Table 5.6: 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	0.047 (0.050)	0.000 (0.000)	0.022 (0.015)	-0.003 (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 plans to attend graduate school, and (IV) whether the student assisted a professor with their research. Res. Cat. faculty is the percentage of reservation category faculty taught courses taken, and is rescaled to capture a 10 percentage point change (e.g. from 0.50 to 0.60). Student controls include reservation category status, gender, age, parents' education, and academic skills baseline z-scores. The random assignment college sample is used, where each observation is a student-test pair. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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

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 5.6 report estimates for graduate student plans and research work with faculty, respectively. Estimates are small in magnitude and not statistically different from zero. Estimates are similar after controlling for faculty characteristics (see Fairlie et al. (2025b)).

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 I1). The average characteristics of students and faculty are similar. We also find balance on all of the student characteristics. 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 5.7. The proportion of classes taught by reservation category faculty is calculated over all courses taken in the first two years for each student which is when students are randomly assigned to classrooms. We do not detect meaningful 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 academic skills test scores measured at the end of year 2 for our main cohort of students.

Table 5.7: 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 (0.027)	0.020 (0.037)	-0.000 (0.000)	0.007 (0.012)
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 plans to attend graduate school. Res. Cat. faculty is the percentage of reservation category faculty taught courses taken, and is rescaled to a 10 percentage point change (e.g. from 0.50 to 0.60). Student controls include gender, age, and parents' education. The second cohort of students and random assignment college sample are used. 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 collected at the end of year 4 to measure expected graduation (which is likely to be very accurate). 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 detect no meaningful differential effect for reservation category faculty percentage on expected graduation. Finally, for this cohort of students we ask the question about whether they plan on going to graduate school at the end of year 4. Reservation category faculty estimates are not statistically different from zero.

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 do not detect meaningful differences which is consistent with reservation category faculty not being less productive than general category faculty.[26]

5.6 Research Productivity and Service Assignments

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, 2019b).[27] However, some emphasis has been placed recently on research productivity. We examine differences between reservation and general category faculty in the number of publications per year which includes academic international journal articles, domestic journal articles, monographs, and edited volumes. Table 5.8 reports estimates from regressing the number of publications per year on the 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. On average, faculty at engineering and technology colleges in India produce 2.4 publications per year. We do not detect meaningful differences between reservation category and general category faculty in the number of articles published. The point estimate on reservation category faculty is small in magnitude 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 nor does the inclusion of additional faculty characteristics.

[26] Estimates for all outcomes are not sensitive to controlling for faculty characteristics. See Fairlie et al. (2025b).

[27] 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, 2019b).

Table 5.8: 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. Appendix Table J1 reports the same set of specifications 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. For these more rigorous and potentially more time-consuming publications we find similar results for the difference between reservation category and general category faculty.[28]

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 with only 13 percent of faculty receiving funding over the two-year period. Table 5.9 reports results from regressions for funding received by faculty. We find estimates that are small in magnitude and not statistically different from zero for the likelihood of obtaining funding for reservation category faculty relative to general category faculty.

[28] We also collected information on whether these papers were published in journals covered by impact factor indices and also do not find meaningful differences between groups. See Appendix Table J2 and Fairlie et al. (2025a) for more details).

Table 5.9: 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

As a robustness check, we separated 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. For both funding sources, we do not detect meaningful differences between reservation category and general category faculty in the receipt of grants (Appendix Table J3 and Table J4). 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 J5). We find similar results for the reservation category faculty coefficient. The main exception is that we find a negative and statistically significant coefficient for reservation category faculty in the international publications regression.

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 5.10 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, estimates for holding an administrative position are small in magnitude and generally not statistically different from zero (although we find marginal significance when we do not control for faculty qualifications). Controlling for faculty qualifications and characteristics does not change the result.

Table 5.10: 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.7 Heterogeneity in Instructional Productivity by Student Type

We next examine heterogeneity in instructional productivity along the dimension of student's reservation status. 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 reservation category faculty struggle teaching general category students.[29] For the potential to reduce inequality, an important question is whether reservation category faculty have positive relative effects on reservation category students. Reservation category 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 5.11. The main reser-

[29] The qualification thresholds or cutoffs in qualifying exams for university admissions are typically lower for students belonging to reservation category groups. Appendix Table D1 reports estimates of student characteristics from our national sample. We find major differences in family background, course performance, and baseline test scores by the reservation status of students. See Fairlie et al. (2025a) for more details.

vation category faculty coefficient captures the effect for general category students. 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. 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 5.11: 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)
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), and the random assignment college sample is used. All models also control for student fixed effects and course fixed effects, and the same set of faculty controls as Table 5.4. 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. We do not detect meaningful differential effects (positive or negative) of reservation category faculty on the course grades of reservation category students, relative to general category students. The results are not sensitive to the removal of student fixed effects or controls.

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 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. These models combine the common difference-in-difference identification strategy used in the previous literature with our use of random assignment for identification. We report estimates in Table 5.12. Specification I repeats the main specification from Table 5.11 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 reservation category student–reservation category faculty interaction captures the relative performance of reservation category students compared with general category students *with the same faculty*. Specification III replaces faculty fixed effects with classroom fixed effects which subsume faculty fixed effects because each classroom is only assigned one faculty member. 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*. For both models, the reservation category student-faculty interaction does not noticeably change after including these different fixed effects.

Table 5.12: 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)	(0.69)	(0.69)
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), and the random assignment college sample is used. Specification I includes course and student fixed effects, and faculty controls, Specification II includes Course, student, and faculty fixed effects, Specification III includes student and classroom fixed effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.8 Additional Student-Faculty Interaction Regressions

We next examine heterogeneity in teacher-like-me effects across reservation groups (SC, ST, or OBC). We attempt to address this issue in two ways. First, we replace the reservation category student indicator with dummy variables for the combined SC/ST group and OBCs (Table 5.13). We continue to find a slight positive effect of reservation category faculty on course grades for all students, but we find estimates of interactions that are not statistically different from zero 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 5.13: 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)
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), and the random assignment college sample is used. All models also control for student fixed effects, course fixed effects, and faculty controls in line with Table 5.4. 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. The match variable takes the value of 1 if a student-teacher pair belong to the same reservation group (e.g. SC student and SC faculty). Table 5.14 reports estimates. We again find a small positive main effect of being taught by reservation category faculty, and no relative gains or losses for students matched to faculty of the same reservation category group.

Table 5.14: 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	-0.11	-0.11	-0.10	-0.11
	(0.31)	(0.31)	(0.32)	(0.31)
Res. Cat. Faculty	1.42**	1.51***	1.32**	1.32**
	(0.59)	(0.60)	(0.58)	(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), and the random assignment college sample is used. All models also control for student and course fixed effects, and faculty characteristics. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We also investigate whether reservation category faculty have a positive relative effect on educational outcomes for reservation category students beyond the immediate course grade. Reservation category faculty might inspire more interest and motivation, improve deeper learning in engineering, provide role models, and contribute to a sense of belonging to reservation category students. We examine interaction effects on follow-on course grades and test scores (Appendix Table H1 and Fairlie et al. (2025b)), and class attendance, dropout, graduate school plans and working for professors on research projects (Appendix Table H2). Using our second cohort of students, we also estimate interactions for expected graduation with degree and graduate school plans measured at the end of year 4 (Appendix Table I2). We find estimates of interaction effects for all of these educational outcomes that are small in magnitude and not statistically significant. We also do not detect a meaningful effect of reservation category faculty on general category students. See Fairlie et al. (2025a) for more details.

6 Conclusion

Although the evidence is limited, affirmative action programs, especially those involving strict quotas, 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 disadvantaged 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. We examine an extensive set of measures of faculty qualifications and productivity capturing education, teaching, research and service 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 do not detect meaningful differences in instructional quality provided by reservation category faculty relative to 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 detect meaningful differences in the amount of time spent on teaching activities, and thus reservation category faculty do not appear to compensate for having lower qualifications by devoting more time to preparing and teaching classes, or advising and tutoring students.

Our estimates of differential faculty effects on longer-term educational outcomes are quite consistent across several measures. For example, we do not detect meaningful differences between faculty types on follow-on course grades, and academic skills, computer science, and electrical engineering tests. The findings rule out the possibility of "teaching to the test" and are consistent with reservation category faculty not being inferior at teaching higher-order engineering skills. Furthermore, we do not detect meaningful differences in 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 we also examine faculty's research productivity and administrative service. The estimates of differences in research and service productivity are small in magnitude and not statistically different than zero.

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.[30] 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. Potential discrimination in the broader uncovered labor market might "push" higher-ability (e.g. more enthusiastic, 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.[31] Our findings speak not only to the debate surrounding affirmative action in faculty hiring, but also to the broader system of affirmative action system in Indian education, since we are examining the relative productivity of two groups of faculty- one hired through a quota system and one hired without quotas, in a setting where an equally aggressive quota system at the student level produces candidates who otherwise may not have been able to furnish the minimum qualifications required to apply for these jobs.

In education, several previous studies find large, positive "teacher-like-me" effects by which teach-

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

[31]See (BBC News, 2015; The New York Times, 2015; The New York Times, 2022). The use of disadvantaged 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 a 2022 Supreme Court of India case directing IITs to follow reservation policies. Recent evidence indicates that they are generally not following quotas in hiring faculty (Paliwal, 2023).

ers from underrepresented racial groups improve the academic outcomes of similar students that they teach.[32] In our analysis of heterogeneity of instructional productivity, we do not find statistically significant "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, disadvantaged 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).

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.[33] 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.

Data Availability

Data and code replicating the tables and figures in this article can be found in Fairlie, Khanna, Loyalka, and Sachdeva (2025c) in the Harvard Dataverse. Link: https://doi.org/10.7910/DVN/N2NKEG.

[32] 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.

[33] 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	8.23	5.99	2.24***
	SD	5.25	5.07	(0.02)
	n	72526	145687	
Proportion Graduating High School (%)	Mean	33.07	17.98	15.09***
	SD	47.05	38.40	(0.20)
	n	72530	145704	
Proportion Graduating College (%)	Mean	21.72	10.51	11.21***
	SD	41.23	30.67	(0.17)
	n	72530	145704	
Proportion with Master's or Higher (%)	Mean	5.58	2.27	3.31***
	SD	22.95	14.88	(0.09)
	n	72530	145704	
Proportion with Master's or Higher (%) (Age 25-50)	Mean	5.87	2.48	3.39***
	SD	23.51	15.55	(0.11)
	n	57327	118528	
Proportion with Regular Employment (%)	Mean	19.78	15.57	4.22***
	SD	39.84	36.26	(0.18)
	n	72530	145704	
Monthly Per Capita Consumption Expenditure (Rs)	Mean	10488.05	7697.75	2790.30***
	SD	8921.50	6458.68	(37.20)
	n	72519	145700	
Weekly Wages (Rupees)	Mean	3197.27	2016.77	1180.50***
	SD	3579.61	4051.90	(33.62)
	n	17420	41607	
Weekly Wages of College Graduates (Rupees)	Mean	5369.71	4305.52	1064.19***
	SD	4597.40	2996.43	(66.81)
	n	6417	7679	
Weekly Wages of College Graduates (Age 25-35) (Rupees)	Mean	4079.10	3194.89	884.20***
	SD	3546.16	2453.96	(82.35)
	n	2518	3370	

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	43.8%	56.2%
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 Student Differences by Reservation Category

Table D1: 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 academic skills score	-0.10	0.12	-0.22*** (0.02)	8748
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 academic skills test scores are z-scores standardized across all respective test takers. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

E Value-Added Measures of Faculty Productivity

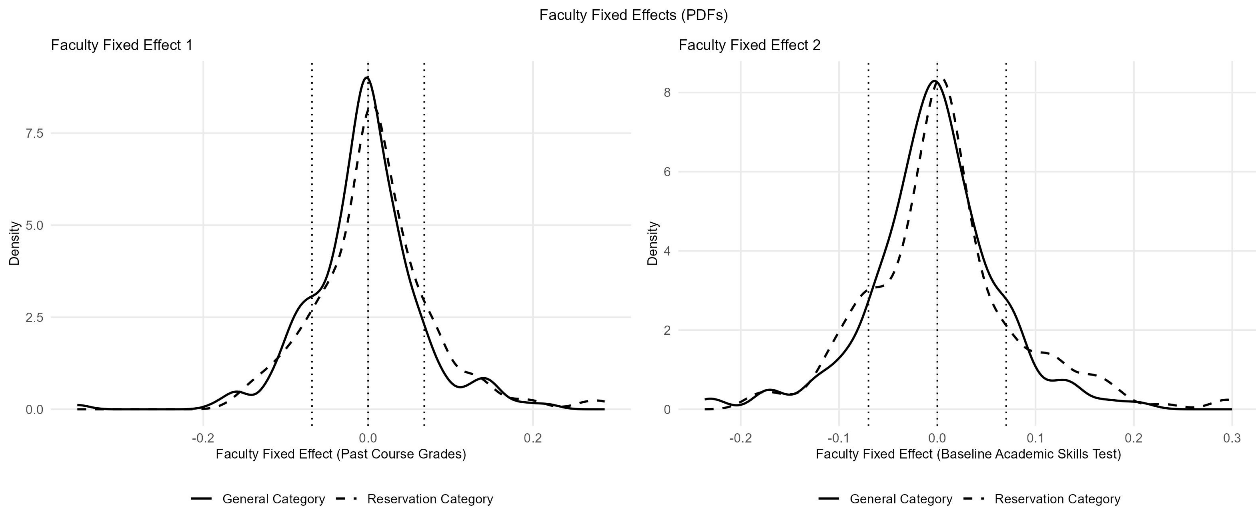

Figure E1: PDF's of Faculty Fixed Effects

Note: Faculty Fixed Effect 1 uses past course grades as a baseline. Faculty Fixed Effect 2 uses test scores from the academic skills test conducted at the beginning of the study as a baseline. The dotted lines plot the mean, mean+ 1 sd, and mean - 1 sd

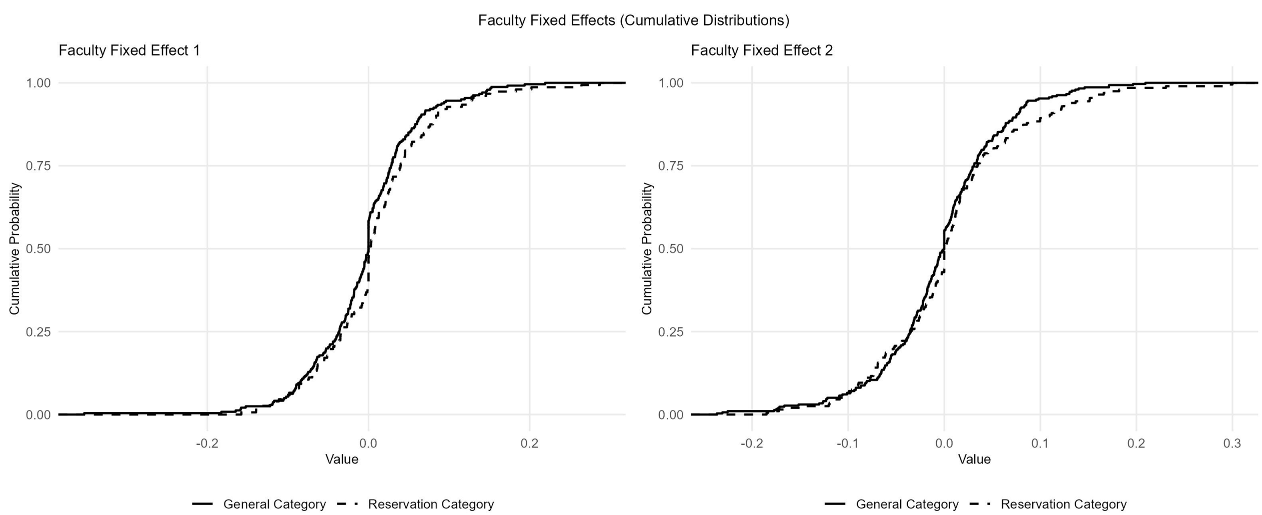

Figure E2: CDF's of Faculty Fixed Effects

Note: Faculty Fixed Effect 1 uses past course grades as a baseline. Faculty Fixed Effect 2 uses test scores from the academic skills test conducted at the beginning of the study as a baseline.

F Differences in Teaching Practices and Time Spent on Teaching Related Activities

Table F1: 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)
Mean	3.14	2.89	6.71	12.33	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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F2: 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)
Mean	9.90	3.62	8.47	4.28
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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

G Robustness Checks

G.1 Main Results without Student Fixed Effects

Table G1: 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

G.2 Inverse-Weighted Observations by Classroom Size

Table G2: 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors are clustered at faculty level.

G.3 Differences in Quality of Instruction: Disaggregated Reservation Groups

Table G3: Regressions for Student Course Grades Measuring Quality of Instruction Weighting Each Classroom the Same, Reservation vs. General Category Faculty

	I	II	III	IV
OBC Faculty	1.22**	1.33**	1.15*	1.19*
	(0.62)	(0.63)	(0.62)	(0.62)
SC/ST Faculty	2.19**	2.18**	1.95**	1.85**
	(0.93)	(0.92)	(0.92)	(0.91)
Associate Professor		0.50	1.16	1.19
		(0.75)	(0.85)	(0.84)
Professor		1.40	2.87**	3.09**
		(0.92)	(1.36)	(1.33)
Experience in years		-0.02	-0.02	-0.01
		(0.05)	(0.05)	(0.05)
Highest degree is PhD			-2.35*	-2.52**
			(1.20)	(1.17)
Highest degree is PhD in progress			-0.82	-0.99
			(0.82)	(0.83)
Degree college elite			0.38	0.31
			(0.59)	(0.58)
Female				1.06*
				(0.57)
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. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors are clustered at faculty level.

H Heterogeneity in Teachers' Effectiveness by Students Type

Table H1: 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 Academic Skills (z-score)
Res. Cat. Faculty	0.900	0.964	0.005
	(2.413)	(1.165)	(0.013)
Res. Cat. Student			-0.337***
			(0.063)
R.C. Faculty × R.C. Student	-0.392	0.306	0.011
	(2.640)	(1.587)	(0.013)
Student controls	FE	FE	Yes
Faculty controls	Yes	Yes	Yes
Mean	51.84	51.67	-0.005
N	23191	11693	2181

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, and (III) standardized scores for an academic skills test administered at the end of the first two years. For Specifications III, 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table H2: 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 independent variables. Student controls include gender, age, parents' education, and academic skills 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. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

I Characteristics and Outcome Regressions for Second Cohort of Students

Table I1: 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 academic skills score	-0.001	1.00	-0.011	0.014
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 I2: 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	-0.002	-0.00008	0.010
	(0.033)	(0.051)	(0.00011)	(0.013)
Res. Cat. Student	-0.293**	-0.146	-0.00028	0.033
	(0.136)	(0.140)	(0.00047)	(0.051)
R.C. Faculty × R.C. Student	0.022	-0.060*	0.00002	-0.008
	(0.026)	(0.033)	(0.00008)	(0.010)
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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

J Extra Measures of Research

Table J1: 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	0.03
	(0.07)	(0.06)	(0.06)	(0.06)
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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table J2: 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 J3: 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 J4: 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 J5: 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: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.