American Economic Journal: Economic Policy 2012, 4(4): 146–168
http://dx.doi.org/10.1257/pol.4.4.146

Discrimination in Grading[†]

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We report the results of an experiment that was designed to test for discrimination in grading in India. We recruited teachers to grade exams. We randomly assigned child "characteristics" (age, gender, and caste) to the cover sheets of the exams to ensure that there is no relationship between these observed characteristics and the exam quality. We find that teachers give exams that are assigned to be lower caste scores that are about 0.03 to 0.08 standard deviations lower than those that are assigned to be high caste. The teachers' behavior appears consistent with statistical discrimination. (*JEL* I21, J13, O15, O17, Z13)

Numerous studies have documented what is known as the Pygmalion effect, in which students perform better or worse simply because teachers expect them to do so (see, for example, Rosenthal and Jacobson 1968). In the modern education system, such expectations are set not just by teachers but by a range of evaluators, many of whom have no direct contact with the student, such as admissions officers or the anonymous graders of national and standardized exams. Of particular concern is whether the resulting experiences of students differ systematically based on observable characteristics, like minority status and gender. Such discrimination could have long-lasting effects, by reinforcing erroneous beliefs of inferiority (Steele and Aronson 1998; Hoff and Pandey 2006), and discouraging children from making human capital investments (Mechtenberg 2009; Tajfel 1970; Arrow 1972; Coate and Loury 1993). Additionally, since such external evaluations are often used to determine access to academic opportunities like competitive schools and higher education, such discrimination could directly block access to these important resources.

Unlike teaching, however, external evaluations take place away from the classroom, making it feasible to restrict the information available to evaluators. Teachers can often deduce the race of a student from physical characteristics observed in the

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[†] To comment on this article in the online discussion forum, or to view additional materials, visit the article page at http://dx.doi.org/10.1257/pol.4.4.146.

classroom, but this information can be removed from an exam, for example, before it is graded. Thus, concerns have entered the discussions on grading standards both because the expectations conveyed through them affect student achievement (Figlio and Lucas 2004) and because more formalized grading strategies may result in a less equitable distribution of scores (Brennan et al. 2001; Gallagher 1998).

Unfortunately, it is difficult to empirically test whether discrimination exists. Disadvantaged minorities, by definition, come from disadvantaged backgrounds with many characteristics that are associated with poor academic performance—few educational resources in schools, low levels of parental education, etc. Thus, it is hard to understand whether children from disadvantaged minority groups perform worse due to discrimination or due to other characteristics. Moreover, as Anderson, Fryer, and Holt (2006) discuss, "uncovering mechanisms behind discrimination is difficult because the attitudes about race, gender, and other characteristics that serve as a basis for differential treatment are not easily observed or measured."

In this study, we designed an experiment to investigate discrimination in grading. We implemented an exam competition in which we recruited children to compete for a large financial prize (US$58 or 55.5 percent of the parents' monthly income). We then recruited local teachers and provided each teacher with a set of exams. We randomly assigned the child "characteristics" (age, gender, and caste) to the cover sheets of the individual exams that were to be graded by the teachers in order to ensure that there would be no systematic relationship between the characteristics observed by the teachers, and the quality of the exams. Therefore, any effect of the randomized characteristics on test scores can be attributed to discrimination.

Within the education literature, our work builds upon a rich body of research in the United States that evaluates teachers' perceptions of African American and female students (see Ferguson 2003, for a thorough literature review). Our methods closely correspond to recent field experiments that have measured racial discrimination in labor market settings, typically in the hiring of actual applicants. The researchers either have actual individuals apply for jobs (Fix and Struyk 1993), or they may submit fictitious job applications to actual job openings (Bertrand and Mullainathan 2004; Banerjee et al. 2009; Siddique 2008). Under both strategies, the "applicants" are statistically identical in all respects, except for race or caste group. Unlike pure laboratory experiments, in which individuals are asked to perform assessments in a consequence-free environment, an advantage of these experiments is that they measure the behavior of actual employers making real employment decisions.

The early literature on discrimination in grading practices focuses on small-scale lab experiments. Subjects were asked to hypothetically evaluate tests, essays, or other student responses for which the researcher has experimentally manipulated the characteristics of the student to whom the work is attributed. Many of these early studies find evidence of discrimination. For example, DeMeis and Turner (1978) find discrimination against African Americans, while Jacobson and Effertz (1974) find evidence of reverse discrimination with unsuccessful females being criticized less harshly than males when failing a leadership task. However, this literature also finds evidence that discrimination varies by who does the grading (Coates 1972; Lenney, Mitchell, and Browning 1983), the type of work being evaluated (Wen 1979), and the underlying quality of the individual's application (Deaux and Taynor

1973). Compared to our methodology, many of these older studies have limited sample sizes and ask graders to assign hypothetical grades. Like the labor market studies, our design places graders in an environment in which their grades have a material effect on the well-being of a child because the graders know they determine the awarding of the prizes.

The second, more recent, strand of the literature compares scores obtained from non-blind grading to scores awarded under blind grading using observational data.[1] Much of this literature tends to find results that contradict the earlier experimental evidence from the lab, finding no discrimination for minority students (Shay and Jones 2006; Dorsey and Colliver 1995; Baird 1998; Newstead and Dennis 1990). Recent exceptions include Lavy (2008), who finds that blind evaluations actually help male students; and Botelho, Madeira, and Rangel (2010), who find evidence of discrimination against black children in Brazil. While these studies provide important evidence, the same exams are usually not graded by the same grader or even using the same grading framework, requiring the researcher to infer differences in grading practices by comparing the distribution of scores between two different measures of student performance. We compare the same exams graded under non-blind grading, holding the individual grader, and all but the characteristics of the student, constant.

On the whole, we find evidence of discrimination against lower caste children. Teachers give exams that are assigned to "lower caste" scores that are about 0.03 to 0.08 standard deviations lower than exams that are assigned to "high caste." These differences are practically very small. They represent, at most, a difference in exam scores of 1.5 percentage points and given the observed test scores distribution, a reduction in score of this magnitude would only slightly change a students' rank in the distribution. On average, we do not find any evidence of discrimination by gender or age.

The data appear consistent with statistical discrimination. Graders tend to discriminate more against children who are graded early in the evaluation process, suggesting that graders utilize demographic characteristics when the testing instrument or grade distribution are more uncertain. If the graders were purely taste-discriminating, there would be little reason to expect that discrimination would vary by the order in which they graded the exam.

We find no evidence that the subjectivity of the test mattered: in fact, graders made "less subjective" subjects, such as math, "more" subjective by being generous with partial credit. Finally, we do not find evidence of in-group bias on average. In fact, we observe the opposite, with discrimination against the low-caste children being driven by low-caste graders, and graders from the high-caste groups appearing not to discriminate at all (even when controlling for the education and age of grader).

Taken together, these findings offer new insights into discrimination in grading. First, the results suggest that if discrimination exists in the subtle grading of an exam,

[1] Outside of the education context, Goldin and Rouse (2000) find that the adoption of blind auditions for symphony orchestras increase the proportion of hired women. Blank (1991) finds no evidence of gender discrimination when submissions to *The American Economic Review* are refereed with or without knowledge of the author's identity.

other more blatant forms of discrimination may exist in the educational system as well. Second, we shed light on the channels through which discrimination operates, so that these findings can help inform the design of future anti-discrimination policies. For example, given that the graders appear to statistically discriminate, policies aimed at making graders more confident in the testing techniques may, perhaps, reduce the dependence on child characteristics while grading.

The paper proceeds as follows. Section I provides some background on caste discrimination and education in India, and articulates our conceptual framework. Section II describes the methodology, while Section III describes the data. We provide the results in Section IV. Section V concludes.

I. Background and Conceptual Framework

A. *Caste Discrimination in India*

In India, individuals in the majority Hindu religion were traditionally divided into hereditary caste groups that denoted both their family's place within the social hierarchy and their professional occupation. In order of prestige, these castes were the Brahmin, Kshatriya, Vaishya, and Shudra respectively denoting priests, warriors/nobility, traders/farmers, and manual laborers.

In principle, individuals are now free to choose occupations regardless of caste, but like race in the United States, these historical distinctions have created inequities that still exert powerful social and economic influences.[2] Given the large gap in family income and labor market opportunities between children from low and high castes, it is not surprising that children from traditionally disadvantaged caste groups tend to have worse educational outcomes than those from the more advantaged groups. For example, Bertrand, Hanna, and Mullainathan (2010) show large differences in the entrance exam scores across caste groups entering engineering colleges, while Holla (2008) shows similar differences in final high school exams.

While it is difficult to identify the influence of caste separately from poverty and low socioeconomic status, the potential for discrimination in schools is significant. Student populations can be diverse and both urban and rural schools maintain detailed records of their students' caste and religion, along with other demographic information such as age, gender, and various information on their parents (see, for example, He, Linden, and MacLeod 2008). Anecdotal evidence suggests that teachers may use this information. For example, the Probe Report of India (1999) cites cases of teachers banning lower-caste children from joining school, and Shastry and Linden (2009) show that caste is correlated with the degree to which teachers exaggerate the attendance of students in conditional cash transfer programs.

[2] Banerjee and Knight (1985), Lakshmanasamy and Madheswaran (1995), and Unni (2007) give evidence of inequality across groups by earnings, while Rao (1992), Chandra (1997), and Munshi and Rosenzweig (2006) show evidence of inequality in social and economic mobility. Deshpande and Newman (2007), and Madheswaran and Attewell (2007) provide some evidence of discrimination in earnings, while Siddique (2008), and Jodhka and Newman (2007) document discrimination in hiring practices.

B. *Conceptual Framework*

We explore three main theories of discrimination in this paper. First, we aim to distinguish between behaviors that are consistent with *taste-based* models of discrimination, in which teachers may have particular preferences for individuals of a particular group or characteristic (Becker 1971), and *statistical* discrimination, in which teachers may use observable characteristics to proxy for unobservable skills (Phelps 1972; Arrow 1972).

One might think that the process of grading would limit statistical discrimination in practice, as teachers observe a measure of skill for the child, i.e., the actual performance on the exam. However, this may not be the case. First, the teacher may be lazy and may not carefully study each exam to determine its quality. Instead, he or she may just use the demographic characteristics as a proxy for skill. Second, teachers may statistically discriminate if they are not confident about the testing instrument. In particular, teachers may be unsure as to what the final distribution of grades "should" look like, and therefore, they may not know how much partial credit to give per question. Thus, teachers may use the demographics, not as a signal of performance, but rather as a signal of where the child should place in the distribution.

Our design allows us to test the different implications of these models.[3] For example, if teachers practice taste-based discrimination, the level of discrimination should be constant regardless of the order in which the exam is graded. On the other hand, we would expect that grades are correlated with exam order if there is statistical discrimination—more discrimination at the end if teachers are lazy and more discrimination at the start if teachers are unsure about the testing instrument and/or the distribution of exam scores.

Second, we explore whether discrimination is more likely to occur in subjective subjects. The introduction of objective tests (particularly multiple choice exams) has been championed as a key method for reducing teacher discrimination. However, these types of tests are not without their detractors, particularly because objective exams are limited in their ability to capture certain types of learning (see, for example, Darling-Hammond 1994; Jae and Cowling 2009). We explore whether teachers are less likely to discriminate when grading exams in relatively objective subjects (like math and Hindi) than subjective subjects (like art).

Finally, we test for the presence of in-group bias, i.e., positive bias toward members of one's own group (see Anderson, Fryer, and Holt 2006, for a review). For example, teachers' beliefs about the average characteristics and capabilities of children from different castes may be influenced by their own membership in a particular caste. One might imagine that lower-caste teachers would be less likely to use caste as a proxy for performance given their intimate experience with low-caste status or alternatively that they might be partial towards people from their own social

[3] There are very few empirical papers that have tested for the presence of statistical and/or taste-based discrimination. These include, but are not limited to: Altonji and Pierret (2001), which finds evidence of statistical discrimination based on schooling, but not race; Han (2004), which performs a test for taste-based discrimination in the credit market and cannot reject the null hypothesis of the nonexistence of taste-based discrimination; Levitt (2004), which finds some evidence of taste-based discrimination against older individuals; and List (2004), which finds evidence of statistical discrimination in the sports cards market.

group. However, there are arguments against in-group bias: for example, low-caste teachers may have internalized a belief that different castes have different abilities, and thus such teachers may discriminate more against low-status children. In laboratory experiments, subjects often exhibit behaviors that are consistent with in-group bias.[4] We explore whether low-caste teachers are more likely to discriminate in favor of low-caste children.

II. Methodology and Data

A. Experimental Design

The experiment is comprised of three components: child testing sessions, the creation of grading packets, and teacher grading sessions. Each component is described in depth below.

Child Testing Sessions.—In April 2007, we ran exam tournaments for children between seven and 14 years of age. Our project team went door to door to invite parents to allow their children to attend a testing session to compete for a 2,500 rupee prize (about US$58).[5] Families were informed that the prizes would be distributed to the highest scoring child in each of the two age groups (7 to 10 years of age, and 11 to 14 years of age), that the exams would be graded by local teachers after the testing sessions, and that the prize would be distributed after the grading was complete. The prize is relatively large, given that the parents earn an average of 4,500 rupee per month (US$104).[6]

Over a 2-week period, 69 children attended 4 testing sessions. The sessions were held in accessible locations such as community halls, empty homes, or temples to ensure that they did not conflict with the school day, and that parents would be able to accompany their children. During the testing sessions, the project team obtained informed consent, and then administered a short survey to the parents in order to collect information on the child and the basic demographic characteristics of the family.

[4] A series of experiments in the psychology literature have found that individuals presented in-group bias even in artificially constructed groups (Vaughn, Tajfel, and Williams 1981) or groups that were randomly assigned (Billig and Tajfel 1973). Turner and Brown (1978) studied "in-group bias" when "status" is conferred to the groups, and found that while all subjects were biased in favor of their own group, the groups identified as superior exhibited more in-group bias. More recently, Klein and Azzi (2001) also find that both "inferior" and "superior" groups gave higher scores to people in their own group. In addition, using data from the game show "The Weakest Link," Levitt (2004) finds some evidence that men vote more often to remove other men and women vote more for women.

[5] For recruitment, our project team mapped the city, collecting demographic information about each community. To ensure that children of varying castes would be present at each session, the team then recruited from neighborhoods with many caste groups, or from several homogenous caste neighborhoods.

[6] The formula for awarding the prize affects the probability that a given child will benefit from the competition. If teachers used this information in conjunction with their initial assessments of an exam's quality, the prize structure may even affect the level of discrimination experienced by different students. For example, our mechanism makes the grading of higher quality exams more important than the grading of low quality exams because only the highest quality exams can receive the prize. It is possible that graders may make an initial (though noisy) assessment of an exam and then decide how much effort to spend grading. When grading, they may even choose to rely more on stereotypes for exams that they believe have no chance of winning. This is an important question for future research.

Next, the project team administered the exam. We included questions that tested standard math and language skills, as well as an art section. Math was selected as the most objective section, covering counting, greater than/less than, number sequences, addition, subtraction, basic multiplication, and simple word problems. Language, which was chosen to be the intermediately objective section, included questions on basic vocabulary, spelling, synonyms, antonyms, and basic reading comprehension. Finally, the art section was designed to be the most subjective: children were asked to draw a picture of their family doing their favorite activity and then to explain the activity. The exam took about 1.5 hours. All parents and children were told that they would be contacted with information about the prize when grading was completed.

Randomizing Child Characteristics.—Typically, one can only access data on the actual grades teachers assign to students whose characteristics the teachers know. This makes it difficult to identify what grade the teacher would have assigned had another child, with different socioeconomic characteristics, completed the same exam in an identical manner. To solve this problem, we randomized the demographic characteristics observed by teachers on each exam so that these characteristics are uncorrelated with exam quality. (Henceforth, we refer to the characteristics that are randomly assigned as the "assigned characteristics" and the characteristics of the child actually giving the exam as the "actual characteristics.") Thus, any correlation between the assigned characteristics and exam scores is evidence of discrimination.

Each teacher was asked to grade a packet of exams. To form these packets, each completed test was stripped of identifying information, assigned an ID number, and photocopied. Twenty-five exams were then randomly selected to form each packet, without replacement, in order to ensure that the teacher did not grade the same photocopied test more than once. Each exam in the packet was then given a coversheet, which contained the randomly assigned characteristics: child's first name, last name, gender, caste information, and age.[7] Each exam was graded by an average of 43 teachers.

As explained in Section I, one of the main limitations of existing studies that compare blindly and non-blindly graded exams is that they have to compare across different graders using different grading standards. We designed our study to allow for the inclusion of grader fixed effects by stratifying the assignment of the exams, and assigned child characteristics to ensure an equal distribution for each grader. Since many last names are caste specific, we randomized the last name and the caste together. Similarly, first name and gender were randomized together.[8] For each teacher, we sampled the child's name without replacement so that the teacher did not grade two different exams from the same child.

[7] We also include caste categories (General, Other Backward Caste, Scheduled Caste, and Scheduled Tribe), which are groupings of the caste. We find small effects of discrimination against the lower categories, but while the magnitude is the same across all coefficients, it is only statistically significant when including the blind test score. Disaggregating by category, the effect is driven by the scheduled caste category. Given the overlapping in categories and caste, we cannot isolate different effects between these two groupings.

[8] This strategy has the advantage of consistently conveying caste. It does prevent us from identifying the specific channel through which teachers get the information. It may be possible, for example, that the name alone is enough to convey caste.

The assigned characteristics were each drawn from an independent distribution. Caste was assigned as follows: 12.5 percent of the exams were assigned each to the highest caste (Brahmin) and the next caste (Kshatriya), while 50 percent of the exams were assigned to the Vaishya Caste, and 25 percent were assigned to the Shudra Caste.[9] We randomly selected the ages of the students from a uniform distribution between 8 and 14, and ensured that gender was equally distributed among the males and females.

Teacher Grading Sessions.—We next recruited teachers to grade the exams. We obtained a listing of the city's schools from the local government and divided them into government and private schools. For each category, we ranked the schools using a random number generator. The project team began recruitment at the schools at the top of the list and approached schools until they obtained the desired number of teachers.[10] In total, the project team visited about 167 schools to recruit 120 teachers, 67 from government schools, and 53 from private schools.

The recruitment proceeded as follows. First, the project team talked with the school's headmaster to obtain permission to recruit teachers. Once permission was obtained, the team invited teachers to participate in a study to understand grading practices, where they were told that they would grade 25 exams in return for a 250 rupee (about US$5.80) payment. The team also informed the teachers that the child who obtained the highest overall score would receive a prize worth 2,500 rupees (about US$58). This prize was designed to ensure that the grades had real effects on the well-being of the children, just as the grades assigned by external graders also have a direct impact on things like the receipt of a scholarship or school admissions.[11]

Each grading session lasted about two hours. The project team provided the teachers with a complete set of answers for the math and language sections of the test, and the maximum points allotted for each question for all three test sections. The team went through the answer set question by question with the teachers. Teachers were told that partial credit was allowed, but the team did not describe how it should be allocated. Thus, the teachers were allowed to allocate partial credit points as they felt appropriate.

Next, the teachers each received 25 randomly selected exams—with the randomly assigned cover sheets—to grade, as well as a "testing roster" to fill out. To ensure that teachers viewed the cover sheets, we asked them to copy the cover sheet information onto the grade roster. They were then asked to grade the exam, and enter the grades onto the roster. When a teacher finished grading, the project team

[9] In addition to being classified into the four large castes, Indian citizens can also be assigned to several affirmative action categories. These are Scheduled Tribe, Scheduled Caste, and Otherwise Backward Castes. The purpose of the distribution of castes was to ensure variation in both caste and the caste categories to which children could be assigned. These categories are restricted to the lowest two castes. The result of ensuring equal distribution among each category was that 75 percent of exams were assigned to the lowest two castes.

[10] Overall, about half of the schools that were approached had teachers that agreed to participate. Generally, teachers cited being busy or a lack of interest as reasons for declining our offer.

[11] These results may also have implications for the behavior of teachers in the classroom. However, the incentives in this study are, of course, not identical to those experienced in the classroom. In the classroom, teachers know much more about a child than is available on our cover sheets, and teachers have the opportunity to interact repeatedly with students over the course of the school year.

administered a short survey to the teacher, which was designed to learn their demographic characteristics and teaching philosophy.

After all the grading sessions were completed, we computed the average grade for each child across all teachers who graded his or her exam. We then awarded the prize to the highest scoring child in each of the age categories based on these average grades.

B. *Data Description*

We collected two sets of exam scores. The first set includes the test scores generated by each teacher. In addition, a member of the research staff graded each exam on a "blind" basis, with no access to the original characteristics of the students taking the exam or any assigned characteristics. This was done to provide an objective assessment of the quality of the individual exam. Note that while the blind grading was meant to mimic the teacher's grading procedures, it was conducted by a project team member who may have graded differently from the teachers. Finally, note that we normalized the exam scores in the analysis that follows in order to facilitate comparisons with other studies in the literature. Each section and the overall exam score are normalized relative to the distribution of the individual scores for the respective measure.[12]

In addition, we have data from two surveys. First, we have data from the parent survey, which contains information on the family's caste, and the child's gender and age. Second, we have data from the teacher survey, which included basic demographic information, such as the teachers' religion, caste, educational background, age, and gender. In addition, we also collected information on the characteristics of teachers' students. Note that there was almost no variation in these questions—all of the teachers taught low-income students like those in our sample.

C. *Empirical Strategy*

Our primary specification takes the following form:

$$y_{ij} = \beta v_{ij} + \delta z_{ij} + \tau_j w_j + \varepsilon_{ij}, \quad (1)$$

where y_{ij} is the test score assigned to test i by the teacher j and $\mathbf{v}_{ij}$ is a vector that is comprised of the randomly assigned characteristics: age, a dummy variable which indicates that the exam was assigned to a female, and a dummy variable that indicates whether the test was assigned to one of the lower caste groups. In addition, we include grader fixed effects $(\mathbf{w}_j)$ allowing us to hold the graders' individual standards fixed. While the random assignment eliminates the systematic correlation between actual child characteristics and the assigned characteristics, it is possible that small differences in the types of tests assigned to each category will exist in any

[12] We have also estimated the results normalizing relative to the blind test scores. Since this is a linear transformation of the dependent variable, the change only affects the magnitude of the coefficient, and it does not affect the hypothesis tests. However, we obtain similar estimates of the coefficients.

Table 1—Teacher Characteristics

		Caste		Gender		Education	
Characteristic	All (1)	High caste (2)	Low caste (3)	Female (4)	Male (5)	No master's (6)	Master's (7)
Number of teachers	120	81	39	87	33	61	59
High caste	0.68	1.00	0.00	0.75	0.48	0.61	0.75
Female	0.73	0.80	0.56	1.00	0.00	0.67	0.78
Age	35.33	36.77	32.33	36.33	32.67	32.92	37.81
Less than a master's degree	0.51	0.46	0.62	0.47	0.61	1.00	0.00
Private school	0.56	0.49	0.69	0.49	0.73	0.70	0.41

finite sample. To ensure that our estimates are robust to these small differences, we additionally include a linear control function that includes the actual characteristics of the child $(\mathbf{z}_{ij})$.

III. Descriptive Statistics and Internal Validity

A. Descriptive Statistics

In Table 1, we provide descriptive statistics for the 120 teachers. In column 1, we provide the summary statistics for the full sample. In columns 2 and 3, we divide the sample by the teachers' caste. In columns 4 and 5, we disaggregate the sample by the teachers' gender. Last, we divide the sample by the teachers' education level in columns 6 and 7.

Sixty-eight percent of the teachers belong to the upper-caste group (column 1). They tend to be relatively young (35 years) and female (73 percent). We recruited at both public and private schools, resulting in a fairly equal number of teachers across the two groups, with 56 percent teaching at private schools. About half hold a master's degree. The relationships between the characteristics generally follow the expected patterns: low-caste teachers are more represented in private school positions, less likely to have a master's degree, and more likely to be male (columns 2–3).

In Table 2, we provide summary statistics for the child characteristics. Column 1 contains averages for the actual 69 children, while column 2 contains averages for the assigned characteristics (3,000 exam copies). Standard deviations are provided in parentheses. Panel A provides the percentage of children who belong to the high-caste group, while panel B disaggregates the lower-caste group by specific caste.[13] In our sample, 18 percent of the children actually belonged to the high-caste group, while 12 percent of exams were assigned this characteristic. Despite an effort to recruit

[13] The discussion of disadvantaged castes in India is a controversial and politically charged issue. As a result, there are many varying uses of the term "low caste." For example, most affirmative action programs use a classification system that divides lower cast individuals into three groups designated as Scheduled Castes, Scheduled Tribes, and Otherwise Backward Castes. Rather than taking a position on the correct way to define "low-caste" individuals, we follow the results presented in online Appendix Table 4. These results indicate that relative to the highest caste, Brahmin students, all other students seem to experience similarly small levels of discrimination. As a result, we group these three castes together in our "low-caste" variable.

Table 2—Child Characteristics

	Actual (1)	Assigned (2)
Panel A. High caste		
	0.18	0.12
	(0.39)	(0.33)
Panel B. Low caste		
Kshatriya	0.24	0.12
	(0.43)	(0.33)
Vaishya	0.34	0.50
	(0.47)	(0.50)
Shudra	0.06	0.25
	(0.23)	(0.43)
Unknown caste/not Hindu	0.18	
	(0.38)	
Panel C. Other		
Female	0.44	0.50
	(0.50)	(0.50)
Age	10.95	10.98
	(2.04)	(2.00)

Notes: The actual characteristics, listed in column 1, include data on all 69 children who completed a test and a demographic survey. Column 2 provides data on the randomly assigned characteristics. This column summarizes the data from the 3,000 coversheets in the study (25 for each of the 120 teachers).

children from the lowest caste, only six percent originally come from the Shudra group. Since we were interested in the effects on this specific subgroup, we increased the observed tests in this category to 25 percent. As shown in panel C, the mean actual age (10.95 years) is approximately the same as the mean assigned age (10.98 years). To maximize power, we created equal-sized gender groups, and therefore, there are more females in the assigned sample (50 percent) as compared to the actual sample (44 percent).

Table 3 provides a description of the test scores. Rather than the normalized scores, we provide the scores as the fraction of total possible points here, for easy interpretation. Using the teacher grades (column 1), the children scored a total of 60 percent. They scored the lowest in art (47 percent) and the highest in math (68 percent). The grading of the exam's art section may have been more subjective than the math or language sections because the average score assigned by the teachers (47) is much lower than the scores given by the blind graders (64). The means of the teachers' test scores for the math and language exams are very similar to those of the blind graders (panel B of Table 3).

Moving away from the differences in subjectivity across tests, the data indicate that *regardless* of the subject, teachers do exhibit a fair amount of discretion in grading overall. Figure 1 provides a description of the total test score range (in percentages) per test. Each vertical line represents the range of scores assigned to one of the 69 exams by teachers. The boxes at the center of each line designate the range of the 25th and 75th percentiles, and the individual dots represent extreme outliers. Overall, even excluding the numerous outliers, the score ranges per exam are quite large, indicating that different teachers assigned partial credit very differently to the same exam.

Table 3—Description of Test Scores

	Teacher scores (1)	Blind test score (2)
Panel A. Test score		
Total	0.60	0.63
	(0.18)	(0.18)
Panel B. Test scores, by exam		
Math	0.68	0.70
	(0.22)	(0.23)
Hindi	0.55	0.58
	(0.16)	(0.16)
Art	0.47	0.64
	(0.32)	(0.35)
Observations	3,000	69

Notes: This table summarizes the test scores from the exam tournament. The scores are presented in terms of the percentage of total possible points. Column 1 provides data on the 3,000 exams that were graded by the 120 teachers in the study. Column 2 provides the results from a blind grading of the original 69 exams.

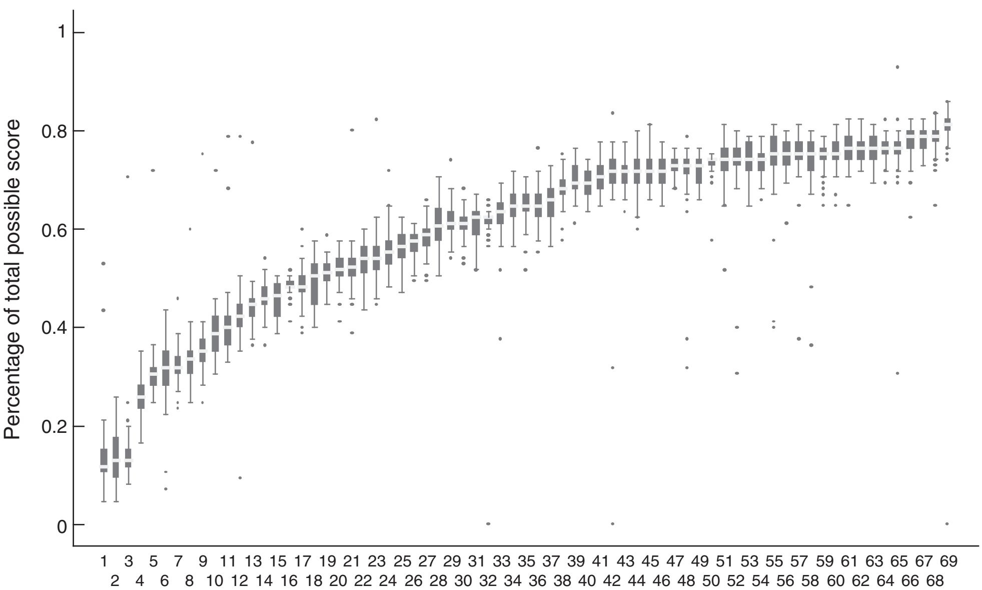

Figure 1. Range per Given Test

Notes: Figure 1 provides the range of test scores (in percentages) given by the teachers for each of the 69 exams used in the study. Each bar provides information for an individual test (the *x*-axis is the test number), and the bar indicates the range of test scores for each test assigned by teachers. The upper and lower ends of each bar are the upper and lower adjacent values and the dots represent outlying values following Tukey (1977).

B. *Do Actual Characteristics Predict Exam Scores?*

In Table 4, we investigate the relationship between the *actual* child characteristics and the exam scores. In column 1, we present the simple correlation between the total test scores from the teachers and the actual characteristics. In column 2, we present this correlation for the blind test score and the actual characteristics.

Table 4—Correlations between Actual Characteristics and Final Test Scores

Test type:	Teacher (1)	Blind (2)
Constant	−5.348	−4.358
	(0.432)***	(2.994)
Low caste	−0.409	−0.427
	(0.028)***	(0.185)**
Female	0.183	0.186
	(0.031)***	(0.213)
Age	0.846	0.675
	(0.082)***	(0.571)
Age^2	−0.030	−0.021
	(0.004)***	(0.027)
Observations	3,000	69

Note: The first column contains results for the total teacher test score, while column 2 contains results for the blind test score.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

The actual characteristics strongly predict the exam scores. As expected, children from the lower caste group score about 0.41 standard deviations worse on the exam than the high-caste group (column 1).[14] Females, on average, score 0.18 standard deviations higher than males. Finally, one additional year of age is associated with an additional 0.85 standard deviations in score, although this effect declines in age. The relationships estimated using the blind score show very similar coefficients (column 2).

C. *Internal Validity*

In Table 5, we test whether the assigned characteristics are correlated to the actual characteristics or quality of the exams. To do so, we regress the actual characteristics (column 1–3) and the blind test scores (columns 4–7) on the assigned characteristics. For each specification, we present the coefficients on each assigned characteristic, as well as the F-statistic and p-value from the joint test for all assigned characteristics. The results demonstrate that the random assignment process succeeded in assigning characteristics to the cover sheets that are, on average, uncorrelated with the actual characteristics or test quality. Out of the 28 comparisons, only three of the coefficients are statistically significant, and all of the coefficients in columns 4–7 are much smaller in magnitude than those observed in Table 4. The joint tests provide further evidence: of the seven estimated equations, only one is statistically significant at the 10 percent level. In particular, as shown in column 4, we find little

[14] Table 1 in the online Appendix replicates Table 4 while disaggregating by specific caste group. Children who belong to Kshatriya caste perform worse (−0.16 standard deviations) than those who belong to Brahman caste, which is the omitted category in the regressions (column 1). Children from the Vaishya caste then score worse than those from the Kshatriya caste by 0.36 standard deviations, and children who belong to the Shudra group score the worst.

Table 5—Randomization Check

	Actual characteristics			Blind scores			
	Low caste (1)	Female (2)	Age (3)	Total (4)	Math (5)	Hindi (6)	Art (7)
Low caste	−0.035	0.006	−0.071	−0.064	−0.062	−0.057	−0.051
	(0.020)*	(0.027)	(0.115)	(0.050)	(0.052)	(0.047)	(0.051)
Female	−0.020	−0.022	−0.022	0.011	0.030	−0.001	−0.018
	(0.014)	(0.018)	(0.075)	(0.034)	(0.036)	(0.032)	(0.034)
Age	−0.063	−0.100	0.053	−0.013	0.044	−0.067	−0.007
	(0.044)	(0.058)*	(0.239)	(0.106)	(0.112)	(0.100)	(0.109)
Age^2	0.003	0.004	−0.003	0.001	−0.002	0.003	−0.000
	(0.002)	(0.003)*	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	3,000	3,000	3,000	3,000	3,000	3,000	3,000
F-Stat	2.1	1.18	0.25	0.44	0.65	0.49	0.89
p-Value	0.0779	0.3184	0.911	0.7787	0.6245	0.7401	0.4704

Notes: This table contains regressions of the actual characteristics of the children of each exam on the characteristics randomly assigned to the coversheet on the copy of the exam that was graded by teachers. The *F*-statistic and *p*-value provide the results of a test of joint significance of the observed characteristics.

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

correlation between all of the assigned characteristics and the quality of the overall exam, as measured by the blind test score (*p*-value of 0.78).[15]

IV. Results

A. *Do Teachers Discriminate?*

In Table 6, we present the results of the regression of the exam scores on assigned caste, gender and age.[16] In column 1, we provide the overall effects of the assigned characteristics on the test scores assigned by the teachers. Given the randomization, we do not necessarily need to include control variables. However, doing so may provide us with greater precision. Therefore, we present the results of specifications in which we control for the actual characteristics (column 2) and then additionally include grader fixed effects (column 3). Finally, we also control for the blind test score (column 4). All standard errors are robust.[17]

As shown in column 1, we find that the teachers gave, on average, the exams assigned to be "low-caste" scores that were 0.084 standard deviations lower than an exam that was assigned to be "high caste" (significant at the ten percent level).[18]

[15] In online Appendix Tables 2 and 3, we disaggregate the exam data by individual caste group. The table further confirms that the randomization was successful.

[16] In Appendix Table 4, we show the results by disaggregated caste groups. We cannot reject the hypothesis that the coefficients on the three observed caste variables are significantly different from one another. Therefore, we grouped the variables together to create the "low-caste" variable.

[17] Common practice is to cluster at the unit of randomization. However, in our estimates, the randomization occurs at the level of the individual observation. As a result, we do not cluster the estimates at a pre-specified level.

[18] It is important to note that in what follows, we can only measure the relative treatment of children in the highest caste to lower caste children. In all specifications, the highest caste children are the omitted category and

Table 6—Effect of Assigned Characteristics on Total Test Scores

Assigned characteristics	(1)	(2)	(3)	(4)
Low caste	−0.084	−0.081	−0.081	−0.026
	(0.048)*	(0.037)**	(0.038)**	(0.013)*
Female	0.020	0.014	0.013	0.008
	(0.033)	(0.027)	(0.027)	(0.010)
Age	0.001	0.003	0.003	0.001
	(0.008)	(0.007)	(0.007)	(0.003)
Actual test characteristics		YES	YES	YES
Grader fixed effect			YES	YES
Blind test score				YES

Notes: This table presents the regression of total normalized test scores on the randomly assigned characteristics. The sample includes the 3,000 graded exams (graded in sets of 25 by 120 teachers).

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

Controlling for child characteristics (columns 2) and teacher fixed effects (column 3) does not significantly affect the estimate on the lower caste indicator variable, but the addition of the controls improves the precision of the estimates, which are now statistically significant at the five percent level. The addition of the blind test score causes the point estimate to fall to −0.026 (column 4). The estimate, however, remains statistically significant at the ten percent level.[19]

Our results suggest that while discrimination may be present, the magnitude of the overall effect is relatively small. While the estimate from our preferred specification in column 3 (including teacher fixed effects and original characteristics control variables) is 21 percent of the 0.41 standard deviation observed gap in performance based on actual characteristics for our sample, this difference is relatively small in absolute terms. It reflects a difference in actual exam scores of only 1.5 percentage points. Relative to the distribution of blind scores, a reduction in score by this magnitude at the median would not change a child's ranking in the distribution at all.[20] It is hard to imagine such differences being noticed by an individual child much less altering the child's self-perceptions. The effect of the observed 0.41 standard deviation gap by actual characteristics would cause the median student to fall to the 38.4th percentile, a decline of 11.6 percentage points.[21]

the indicator variable for the lower castes measures the difference between the lower castes and the highest caste.

[19] Unfortunately, this experiment was not designed to allow the use of test fixed effects. During the random assignment of characteristics to cover sheets and exams to teachers, we ensured that the assignment of exams to teachers was stratified such that each teacher received a distribution of exams with similar characteristics, allowing for the inclusion of grader fixed effects. While we ensured that the quality of exams were equally distributed (Table 5), we were not able to similarly stratify the assignment of characteristics and graders to the individual exams to ensure that each exam was graded by the same types of teachers, and assigned the same distribution of characteristics. As a result, we cannot include exam fixed effects without changing the underlying sample of exams used in the analysis, since some exams were not assigned to some castes or types of graders.

[20] At other points in the distribution, a child's ranking would change, but still by only a small amount. At the 75th percentile, for example, the child's rank would fall by 5.8 percentage points, and at the 25th percentile the child's rank would fall by only 1.5 percentage points.

[21] A student at the 75th percentile would fall by 21.75 percentage points to the 53.25th, and at the 25th percentile a student's rank would fall 5.8 percentage points.

We do not find any effect of assigned gender or age on total test scores, regardless of specification (Table 6).[22] Note that not only are the effects not statistically significant, but also the magnitudes of the effects are very small. Given that there is no effect on either age or gender, we focus the rest of the analysis on caste.[23]

B. *Statistical versus Taste-Based Discrimination*

To understand whether discrimination is correlated with exam order, we randomly ordered the exams in the packet. We can therefore graph the relationship between assigned scores and grading order by caste group (Figure 2). The *x*-axis is the order in which the exams were graded (from 1 to 25). The dotted line signifies the scores for the assigned low-caste group, while the solid line signifies this for the assigned high-caste group. We find a gap in test scores between the assigned low- and high-caste groups at the start of the grading order, but this effect fades as the place in the grading order increases.

We test this in a more formal regression framework in Table 7. In column 1, we control for the order in which the exams were graded and add a term to account for the interaction between the grading order and the assigned characteristics. In column 2, we show the results of the interaction between the assigned characteristics and a variable that indicates that the exam was graded in the first half of a teacher's pile. All regressions include the original test characteristics, the grader fixed effects, and assigned gender and age.

We find that the grading order matters. Independent of order, teachers mark exams that are assigned to be low caste 0.22 standard deviations lower (significant at the one percent level; column 1). As grading order increases, the difference is mitigated. The first exams that are graded by the teachers exhibit a −0.22 standard deviations difference between the high-caste and low-caste exams. By the 25th exam, low-caste exams are treated very much like high-caste exams with a difference of only 0.042 standard deviations. As shown in column 2, being graded in the first half of the packet implies a 0.11 standard deviation gap between the low and high-caste exams, but this is not statistically significant at conventional levels.

[22] It is possible that the teachers could gauge actual gender from visual clues such as handwriting, if we believe, for example, that girls have neater handwriting. However, we have no evidence that this ever happened. No teacher, for example, was reported to have made remarks suggesting that they found the characteristics surprising, such as by noting that a child had "neat handwriting for a boy." Moreover, the existing evidence suggests that this may not be a problem: Lavy (2008) finds that the bias against boys is the same in both subjects where girls can be more easily identified from their handwriting than those where it is harder to deduce gender from the handwriting. It is also possible that the child's actual age is discernible from the exam. For example, a teacher might have received an exam from a young child that was assigned an older age and not believed the assignment, perhaps ignoring age altogether as a result. The data suggest that it would be difficult to infer age from the quality of an exam: for example, a 14-year-old in the sample scored a 28 on the blind test score, which is lower than the minimum blind test score for a seven year-old (41). More generally, a national survey of children aged seven to 14 in India showed that the range of skills of children vary significantly by age (Pratham 2005).

[23] In results not presented in this draft, we also estimate all of the relationships investigated in Tables 7–9 using age and gender, but find no differential treatment across these characteristics. Finally, in online Appendix Table 5, we show the results of specifications where we interact the low-caste indicator variable with the female dummy variable. The sign of the interaction between low caste and female is positive, but the coefficient is indistinguishable from zero.

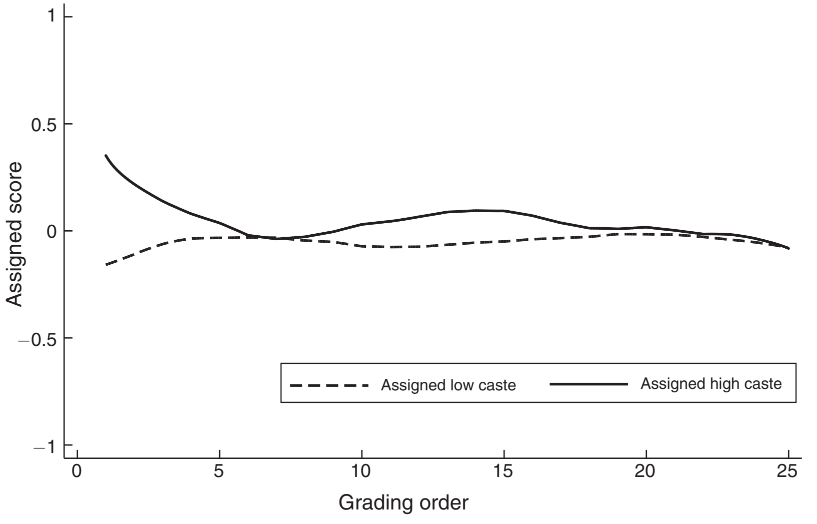

Figure 2. The Caste Gap, by Grading Order

Notes: Figure estimates the relationship between the normalized total score and the order in which the exams were graded. Relationship estimated using a local linear polynomial estimate with an Epanechnikov kernal and a bandwidth of five.

Table 7—Effect on Test Scores, by Grading Order

Assigned characteristics	(1)	(2)
Low caste	−0.222	−0.030
	(0.076)***	(0.052)
Low caste × grading order	0.010	
	(0.005)**	
Low caste × start of grading order		−0.114
		(0.076)
Actual test characteristics	YES	YES
Grader fixed effect	YES	YES

Notes: This table explores whether the order in which the exam was graded affects the treatment of exams assigned to different observable characteristics. The variable "grading order" is the order in which the teachers graded the exams. This variable ranges from 1 (1st exam graded) to 25 (last exam graded). The variable "start of grading order" is an indicator variable that equals one if grading order is less than or equal to twelve, and zero otherwise. The outcome variable is the total normalized score. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).

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

The evidence appears consistent with statistical discrimination.[24] Teachers may statistically discriminate in two ways. First, teachers may be lazy and use statistical

[24] Note that the way in which teachers statically discriminate may either be borne out of statistical actualities or their own tastes of how these groups should fare. For example, if the teachers are statistically discriminating, then we would expect them to use observed age to make predictions about the skills of the child, since the age variable has much more predictive power than caste. However, assigned age does not predict the test scores. Thus, if they are statistically discriminating, then the teachers might have incomplete information, might just be bad at making

discrimination to reduce the amount of time they need to spend grading each exam. While we cannot fully rule out this possiblity, the fact that the teachers knew that a large prize was at stake increased the seriousness of the exercise. When they were confused, the teachers asked the project team questions and all of the teachers spent a fair bit of time grading each exam. Moreover, if teachers were lazy, then we might expect them to mark wrong answers as "0" right away, and not spend time thinking through the answer to determine the correct level of partial credit. In fact, we observed the opposite: teachers gave a considerable amount of partial credit for wrong answers. Finally, we might expect that lazy teachers would discriminate more at the end of the packet, as they become more fatigued from grading. However, this was not the case. Thus, it does not appear as though the teachers were shirking their responsibilities.

Second, teachers may statistically discriminate if there is uncertainty over how to give partial credit, or they would like to give out a certain quantity of "good" scores and they are unsure what the final test score distribution will be. In this case, the teachers may use the characteristics of a child, not as a signal of performance, but rather as a signal of where the child will end up in the distribution. Here, we would expect more discrimination at the start of the exam, when teachers are learning about the exam distribution.[25]

C. *The Subjectivity of the Exam*

It is possible that teachers might not be able to discriminate if they have little leeway in assigning points to the exam questions. Thus, we specifically included subjects on the exam that had different levels of subjectivity.[26] In Table 8, we present the results disaggregated by subject. All specifications include the original test characteristics, grader fixed effects, and assigned age and gender. We do not observe significant differences across the three subjects. Even in the art section, the reduction in test scores for assigned low caste is similar to that of the math section.

To better understand these results, we took a closer look at the points assigned for each question on the exam. We did not give the teachers advice about how to assign points for each question. We only provided guidance on the maximum number of possible points. Despite the fact that the questions on the test were relatively simple, the graders still made an effort to assign students partial credit for the questions on the Hindi section (and also, to a lesser degree, the math section). Therefore, even though the art exam was the most subjective, graders managed to exert discretion over all of the exams.

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statistical predictions as to how children of particular groups will fare on the exams, or might discriminate based on preconceived notions of how different groups should perform.

[25] If teachers are statistically discriminating, then natural repeated interactions in the classroom may reduce discrimination. However, if discrimination early on during the course of the year leads to a self-fulfilling prophesy, statistical discrimination early in the school year may have long lasting effects throughout the school year.

[26] Unfortunately, the order in which teachers graded the exam was always the same: math, Hindi, and then art. Ideally, we would have randomized the order that the teachers graded questions across the exams, but we did not want to confuse the teachers. Thus, it is possible that the teachers learn the "quality" of the child from carefully grading questions early on (i.e., the math section) and this biased their grading of later sections (i.e., the art section). This may bias us against finding differences across subjects.

Table 8—Effect on Test Scores, by Subject

	Math (1)	Hindi (2)	Art (3)
Low caste	−0.077	−0.075	−0.056
	(0.041)*	(0.039)*	(0.038)
Original test characteristics	Yes	Yes	Yes
Grader fixed effect	Yes	Yes	Yes

Notes: This table presents the regression of normalized test scores for the indicated sections of the exam on the randomly assigned characteristics. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

D. *In-Group Bias*

Finally, we explore whether teachers differ in the degree to which they utilized the assigned characteristics when grading. Individuals may discriminate in favor of their own group (in-group bias), and therefore we test if low-caste teachers favor low-caste children. In addition, we estimate whether the degree of discrimination varies by teachers' gender, education level or age, since the literature suggests that these characteristics may also influence the level of discrimination. Specifically, educated teachers may be more aware and tolerant of diversity, whereas older teachers may have more experience teaching students of different backgrounds.

We present the results of our analysis in Table 9. We present the results by caste, gender, master's degree completion, and age in panels A through D, respectively. In column 1, we show the results for the sample that is listed in the panel title, while in column 2, we show the results for the remaining teachers. In column 3, we present the estimated difference between the coefficients.

We do not find evidence of in-group bias. In fact, we observe the opposite. We do not see any difference in test scores between exams assigned to be lower caste and those assigned to be high caste for high-caste teachers (column 1, panel A). However, low-caste teachers (column 2) seem to have discriminated significantly against members of their own group. The difference between low- and high-caste teachers is large—about 0.18 standard deviations—and significant at the five percent level (column 3).[27]

Turning to gender, we observe that female teachers significantly downgrade low-caste exams, while male teachers do not. However, the coefficient of the effects for male teachers is not significantly different than the coefficient for female teachers. Although the coefficients are similar, the sample size of male teachers is much smaller (33 male teachers versus 87 female teachers), increasing the variance in the

[27] Caste rankings are extremely detailed. So, there are lower subgroups even within the low-caste groups. We can observe that generally low-caste graders differentially treat low-caste children relative to high-caste children. A question for future research, which would require a more detailed analysis with a much larger sample size, is to investigate whether teachers are discriminating generally against lower caste students or targeting particular (possibly lower) subgroups.

Table 9—Effect on Test Scores, by Teacher Type

	Belongs to panel title category?		
	Yes (1)	No (2)	Difference (3)
Panel A. Upper caste			
Low caste	−0.021	−0.212	0.184
	(0.047)	(0.063)***	(0.078)**
Panel B. Male			
Low caste	−0.060	−0.088	0.029
	(0.073)	(0.044)**	(0.085)
Panel C. Master's degree			
Low caste	−0.074	−0.084	0.010
	(0.050)	(0.056)	(0.075)
Panel D. Below median age			
Low caste	−0.126	−0.035	−0.092
	(0.050)**	(0.056)	(0.075)
Assigned test characteristics	Yes	Yes	Yes
Grader fixed effect	Yes	Yes	Yes

Notes: This table presents estimates of discrimination disaggregated by the characteristics of the teachers. Estimates presented in column 1 are for tests graded only by teachers who have the characteristics indicated in the panel name. Column 2 contains estimates using only tests for teachers that do not have the indicated characteristic. Finally, column 3 presents an estimate of the coefficient on the interaction of the teacher's characteristic with the indicated observed child characteristics. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers). The outcome in every regression is the normalized total score.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

estimates. Finally, we find no significant difference in caste discrimination by teachers' education or age.

V. Conclusion

While education has the power to transform the lives of the poor, children who belong to traditionally disadvantaged groups may not reap the full benefits of education if graders systematically discriminate against them. Through an experimental design, we find evidence that teachers discriminate against low-caste children while grading exams. For example, we find that the teachers give exams that are assigned to be upper caste scores that are, on average, 0.03 to 0.08 standard deviations higher than those assigned to be lower caste. We do not find any overall evidence of discrimination by gender. The evidence suggests that teachers may be practicing statistical discrimination. On average, we do not find evidence of in-group bias.

The findings from this study provide a clear direction for future research. First, the study suggests that external graders are practicing statistical discrimination when there is more uncertainty over the testing instrument. This could imply that policies designed to increase understanding of an exam may reduce discrimination. Future research should try to determine whether improving confidence and quality through training programs reduces discrimination. Second, graders naturally added subjectivity to "objective" subjects like math through the generous use of partial credit. It is important to understand how graders assign partial credit and whether helping them learn how to better standardize grading mechanisms can reduce discrimination, while still allowing for the flexibility that open-ended questions provide. Finally, if discrimination is present in the subtle art of grading, this suggests that teachers may discriminate through other mechanisms as well. Suitably modified, experiments such as this might be able to capture these other mechanisms through which teachers convey biases.

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