Discrimination in Grading

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Abstract:

In this paper, we report the results of an experiment that was designed to test for the presence of discrimination in grading and to explore the mechanism through which such discrimination might operate. In India, we ran an exam competition in which children compete for a large financial prize, and then we recruited teachers to grade the exams. We randomly assigned child "characteristics" (age, gender, and caste) to the cover sheets of the exams to ensure that there is no systematic relationship between the characteristics observed by the teachers and the quality of the exams. We find that teachers give exams that are assigned to be lower caste scores that are about 0.03 to 0.09 standard deviations lower than those that are assigned to be high caste. The teachers' behavior appears more consistent with statistical discrimination models than taste-based models. Finally, we find that discrimination against low caste students is driven, on average, by low caste teachers.

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I. INTRODUCTION

Numerous studies have documented what is known as the Pygmalion effect, through which students perform better or worse simply because teachers expect them to do so (see for example, Rosenthal and Jacobson, 1968). However, we do not yet understand how teachers formulate or transmit these expectations about student performance. Of particular concern is whether or not teachers systematically treat students differently based on observable characteristics, such as minority status and gender. If this type of discrimination does exist, it could have long lasting effects, by reinforcing erroneous beliefs of inferiority (Steele and Aronson 1995, 1998; Hoff and Pandey, 2006) and discouraging children from making human capital investments (Mechtenberg, 2008; Taijel, 1970; Arrow 1972; Coate and Loury, 1993). Discrimination would, thus, hinder the effectiveness of education in leveling the playing field across children from different backgrounds.

Teachers could convey biases in numerous ways. They could, for example, blatantly treat students differently within the classroom or transmit subtler cues like facial expressions (Feldman and Orchowsky, 1979). The choice of material covered could differentially affect students. Of all of these modes of discrimination, grading has received the most attention historically, both because it is the primary mechanism through which students receive feedback on their performance, and because gateway exams are very important in many countries.

Unfortunately, it is difficult to empirically test whether discrimination exists in the classroom. For example, disadvantaged minorities, by definition, come from disadvantaged backgrounds that exhibit many characteristics that are associated with poor academic performance—few educational resources in schools, low levels of parental education, families with little human or social capital, and even high rates of child labor. Thus, it is hard to understand whether children who belong to these minority groups perform worse in school, on average, because of discrimination or because of 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 paper, we focus on discrimination in grading practices. Specifically, we designed an experiment to investigate discrimination by caste, gender, and age. We implemented an exam competition in which we recruited children to compete for a large financial prize (58 USD 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 aims to evaluate teachers' perceptions of African American and female students (see Ferguson (2003) for a thorough literature review). The early strand of the literature on discrimination in grading practices focused 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 Efferts (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).

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), which finds that blind evaluations actually help male students, and Botelho, Madeira, and Rangel (2010) who find evidence of discrimination against black children in Brazil.

In this study, we aim to improve upon the methods in both these literatures. First, many of these older studies in laboratory have limited sample sizes, restricting the scope of the statistical conclusions that can be drawn. Second, in contrast with the lab experiments where teachers assign hypothetical grades, we place teachers in an environment in which their grades have a material effect on the well-being of a child (they know that the child who wins will receive a large prize).[2] Third, because we are using an experiment rather than relying on observational data, we can test more precisely for the implications of several key models of

[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 *The American Economics Review* are refereed with or without knowledge of the author's identity.

[2] Our methods closely correspond to recent field experiments that have been used to measure racial discrimination in labor market settings. These experiments typically measure discrimination in the hiring of actual applicants. The researchers either have actual individuals apply for jobs (Fix and Struyk, 1994) or they may submit fictitious job applications to actual job openings (Bertrand and Mullainathan, 2004; Banerjee, Bertrand, Datta, and Mullainathan, 2009; Siddique, 2008); in both cases, 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-less environment, a major advantage of these experiments is that they are able to measure the behavior of actual employers making real employment decisions.

discrimination. Specifically, the experiment provides a test to determine whether the teachers are exhibiting behavior that is consistent with taste-based or statistical discrimination. Finally, we also test for variation in discrimination based on the subjectivity of the material and the presence of in-group bias, which relates to whether group members treat other members of their own group preferentially.

On the whole, we find evidence of discrimination against lower caste children, but the magnitude of the effect is small. Teachers give exams that are assigned to “lower caste” scores that are about 0.03 to 0.09 standard deviations lower than exams that are assigned to “high caste.” Compared to the observed differences in student performance by caste, these effects are very small. On average, we do not find any evidence of discrimination by gender or age.

The data are clearly inconsistent with a taste-based discrimination model, and seems to be more consistent with a model of statistical discrimination. Two empirical facts help us distinguish between the two models: First, we find that when we disaggregate the results by the quality of the exam, the low-performing, low caste children lose out, while the low-performing females tend to gain from discrimination. Second, teachers tend to discriminate more against children who are graded early in the evaluation process, suggesting that teachers use demographic characteristics to help grade when the testing instrument or grade distribution are more uncertain. If the teachers were purely taste-discriminating, there would be little reason to expect that discrimination would vary by the order in which the teacher graded the exam. However, the fact that teachers take exam quality into account argues against a model of statistical discrimination whereby teachers are too lazy to spend time grading the exam, and instead assign grades based on characteristics of the children. Rather, these facts points to a model of statistical discrimination in which teachers are unsure about the distribution of test scores at the start of the grading process, so they use the child's characteristics to help place the early exams within a distribution. In sum, this suggests that teachers may have priors about the variance of scores by demographic group, in addition to the mean score by demographic group.

We test for the possibility that discrimination may be more likely in more subjective subjects. However, we find no evidence that the subjectivity of the test mattered: in fact, teachers 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 teachers, and teachers from the high caste groups appearing not to discriminate at all (even when controlling for the education and age of teacher). However, we do find some evidence that both groups of teachers are widening the distribution of scores, providing relatively lower scores to low quality, low caste exams and providing relatively higher scores to high quality, low caste exams.

Taken together, these findings offer new insights into discrimination in the classroom. First, the results suggest that if discrimination exists in the subtle grading of an exam, other more blatant forms of discrimination may exist in the classroom as well. Thus, the results in this paper provide a lower bound effect of the effect of discrimination on child performance. Second, in this paper we shed light on the channels through which discrimination operates, with the goal being that these findings can help inform the design of future anti-discrimination policies within the classroom. For example, we find that teachers statistically discriminate when they are unsure about the testing instrument. Thus, perhaps policies aimed at making teachers more confident in the classroom may help reduce the dependence on child characteristics while grading.

The rest of the paper proceeds as follows. Section II provides some background on caste discrimination and education in India, and articulates our conceptual framework. Section III describes the methodology, while Section IV describes our data. We provide the simple test of discrimination in Section V. In Section VI, we try to understand the nature of discrimination, while Section VII concludes.

II. 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 a 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.[3] Given the large gap in family income and labor market opportunities between children from lower and high caste groups, it is not surprising that children from traditionally disadvantaged caste groups tend to have worse educational outcomes than those from more advantaged groups. For example, Bertrand, Hanna, and Mullainathan (2010) show large differences in the average entrance exam scores across caste groups entering engineering colleges, while Holla (2008) shows similar differences in final high school exams.

[3] Banerjee and Knight (1985), Lakshmanasamy and Madheswaran (1995), and Unni (2002) 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.

While it is difficult to identify the influence of caste separately from poverty and low socio-economic status, the potential for discrimination in schools is significant. 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 take this information into account. For example, the Probe Report of India (1999) cites cases of teachers banning lower caste students from joining school, and Shastry and Linden (2009) show that caste is correlated with the degree to which teachers are willing to exaggerate the attendance of students in transfer programs that are conditional on attendance.

B. Conceptual Framework

There are three main theories of discrimination that we will explore 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).

The empirical design could eliminate the possibility of statistical discrimination in practice, as teachers observe a measure of skill for the child: the actual performance on the exam. However, one can imagine situations where the teacher may still statistically discriminate. First, the teacher may be lazy and may not be invested in carefully studying the exam to determine the skill level for each child. In this case, he or she may choose to use the children's 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 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.

Our design allows us to test the different implications of these models.[4] 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 teachers would discriminate more at the start of the grading process—when there is more uncertainty about the testing instrument and distribution of exam scores—under some forms of statistical discrimination. Moreover, if teachers take the underlying quality of the exam into account when discriminating, this would contradict the "lazy" teacher model.

Second, we will explore whether more discrimination occurs in subjective subjects. The introduction of objective tests (particularly multiple choice exams) has been championed as a key method for reducing a teacher's ability to convey their biases. 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, 2008). In this study, we explore whether teachers are less likely to discriminate when grading exams in objective subjects (like math) than when grading exams in subjective subjects (like Hindi or art).

[4] 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 (2002), which performs a test for taste-based discrimination in the credit market and cannot reject the null hypothesis of the non-existence 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.

Finally, we will test for the presence of in-group bias, i.e. positive bias toward members of your own group (for a good review of the theoretical and empirical literature on in-group bias see Anderson, Fryer and Holt, 2006). 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 group. On the other hand, 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 very low status children. In laboratory experiments, subjects often exhibit behaviors that are consistent with in-group bias.[5] We will explore whether low caste teachers are more likely to discriminate in favor of low caste-students, and whether female teachers are more likely to discriminate in favor of female students.

III. METHODOLOGY AND DATA

In this section, we first describe the methodology that we designed to understand whether discrimination exists in grading. We then discuss the data and lay out our empirical methodology.

A. Research Design

[5] 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 (1976) 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 that some evidence that men vote more often for men and women vote more often for women.

Our experiment comprises three components: child testing sessions, the creation of grading packets, and teacher grading sessions. We first recruited children to participate in a prized exam competition. After the competition, we copied the tests that the children completed and compiled them into grading packets. Each test copy in the grading packet was assigned an information sheet that included randomly assigned demographic characteristics. We then recruited local teachers to participate in grading sessions, during which the teachers graded the exams that displayed the randomly assigned characteristics.

Child Testing Sessions

In April 2007, we ran exam tournaments for children between seven to fourteen 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 Rs 2500 prize (about $US 58).[6] The project team informed the families that prizes would be distributed to the highest scoring child in each of the two age groups (7 to 10 years of age, and 11 to 14 years of age), that the exams would be graded by local teachers after the testing sessions, and that the prize would be distributed after the grading was complete. The prize is a significant sum of money, given that the parents reported earning an average of 4,500 Rs per month ($US 104) in the parent survey that we administered.

Over a two week period, sixty-eight children attended four testing sessions. The testing sessions were held in various accessible locations such as community halls, empty homes or temples. The sessions were held on weekends to ensure that they did not conflict with the school day and that parents would be able to accompany the children to the sessions. During the testing

[6] For recruitment, our project team mapped the city: they collected demographic information about each community and also identified community leaders with whom they might be able to work later in the project. To ensure that children of varying castes would be present at each session, the team tried to either recruit from neighborhoods with many caste groups or from several homogenous caste neighborhoods.

sessions, the survey team first obtained informed consent from the parents for their participation in the parent survey and their child's participation in the tournament. Next, the survey team administered a short survey to the children's parents in order to collect information on the child (gender, age) and also to collect basic demographic characteristics of the family (income background, employment status of the father, and caste information).

After administering the survey, the project team obtained written assent from each participating child and began administering the actual exam. To vary the subjectivity of the exam questions, we included questions that tested the basic math and language skills covered by the standard Indian curriculum, as well as an art section in which the children were asked to display their creativity. The exam took approximately 1.5 hours. All children who participated in the testing session received a reading workbook at the time of the sessions and were told that they would be contacted with information about the prize when grading was complete.

Randomizing Child Characteristics

The key to our experimental design is to break the correlation between the children's actual performance on an exam and the child characteristics perceived by the teacher when grading the exam. In a typical classroom setting, one can only access data on the actual grades teachers assign to students whose characteristics the teachers know. This makes it impossible to identify what grade the teacher would have assigned had another child, with different socio-economic characteristics, completed the exam in an identical manner. Our experimental design allows us to ensure the independence of the exam's quality and the characteristics observed by the teachers.

Specifically, we randomized the demographic characteristics observed by teachers on each exam. Each teacher was asked to grade a packet containing 25 exams. To form these packets, each test completed by a student was stripped of identifying information, assigned an ID number, and photocopied. Twenty-five copies were then randomly selected to form each packet, without replacement, in order to ensure that the same teacher did not grade the same photocopied test more than once. Each exam in the packet was then assigned a socio-demographic coversheet, which contained the basic demographic information for the "child." This included a child's first name, last name, gender, caste information, and age.[7] These child characteristics were randomly assigned from the characteristics of children sitting for the exams. By teacher, we stratified the assignment of the characteristics to ensure that each teacher observed coversheets with the same proportion of characteristics of each type of child, avoiding the possibility that a teacher was assigned to grade children of a single sex or caste. Since most Indian first names are gender specific, the first name and gender were always randomized together. Similarly, many last names are also caste specific and, therefore, we randomized the last name and the caste together.[8] For each teacher, we sampled the name of the child without replacement so that the teacher would not be grading two different exams from the same child.

Caste, age, and gender were each drawn from an independent distribution. We randomly selected the ages of the students from a uniform distribution between eight and fourteen. We ensured that gender was equally distributed among the males and females. Caste was assigned according to the following distribution: twelve and a half percent of the exams were assigned each to the highest caste (Brahmin) and the next caste (Kshatriya), while fifty percent of the

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[7] We also include caste categories (General, Other Backward Caste, Scheduled Caste, and Scheduled Tribe), which are groupings of the caste categories.

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

exams were assigned to the Vaishya Caste and twenty-five percent were assigned to the Shudra Caste.[9]

Each exam was graded by an average of forty-three teachers. Since the "observed" characteristics of the child were randomly assigned, we would expect that these characteristics would be uncorrelated with the exam grade if there were no discrimination. Thus, any correlation between the "observed" characteristics and exam scores is evidence of discrimination.

Teacher Grading Sessions

After creating the packets, we recruited teachers to grade the exams. We obtained a listing of schools in the city from the local government, and we divided the schools 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 went down the list until they obtained the desired number of teachers. 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 headmaster of the school to obtain permission to recruit teachers from the school. Once permission was obtained, the project team explained to the teachers that they would like to invite them to participate in a study to understand grading practices. The teachers were told that they would grade the exams of twenty-five children and that they would be compensated for their work with a Rs 250 (about $US 5.80) payment. The project team also informed the teachers that the child who obtained the highest score based on the grading would receive a prize worth Rs 2500 (about

[9] The purpose of this distribution was originally to ensure variation in both caste and the caste categories to which children could be assigned. These classifications are restricted to the lowest two classes and ensure equal distribution among each category, resulting in 75 percent of the exams being assigned to these castes.

$US 58). This prize was designed to establish incentives for the teachers' grading by ensuring that the grades received on the exam have real effects on the well-being of the children, thereby mimicking the incentives faced by teachers in school.[10]

On average, a grading session lasted about two hours for each teacher. At the sessions, the project team first obtained the teacher's consent. Next, 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 sections of the test. The project team went through the answer set question by question with the teachers. Teachers were told that partial credit was allowed, but the project team did not describe how partial credit should be allocated. Thus, the teachers were allowed to allocate partial credit points as they felt appropriate.

Next, the grading portion of the session began. The teacher received twenty-five 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 demographic information, we asked them to copy the information from the cover sheet onto the grade roster. They were then asked to grade the exam and enter the total score and the individual grades for each section of the exam—math, language, and art—onto the testing roster.

When a teacher finished grading his or her packet of exams, the project team administered a short survey to the teacher. The survey consisted of questions designed to gauge the demographic characteristics and teaching philosophy of each teacher.

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[10] The incentives 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. The main purpose of the prize is to create an environment in which teachers' behavior affects the student – in contrast to experiments in which teachers simply grade exams while knowing that the grades they award have no implications outside of the study.

After all the grading sessions were complete, 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.[11]

B. Data Description

We compiled three sets of data: exam scores, parent surveys, and teacher surveys. 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 using the same grading procedures as the teacher, but on a "blind" basis in which they had 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. The set of exam scores includes the total score and a score on each subject (math, Hindi, and art).

Each subject was selected so as to provide variation in the objectivity with which the individual sections could be evaluated. Math was selected as the most objective section and questions covered counting, greater than/less than, number sequences, addition, subtraction, basic multiplication, basic addition, and simple word problems among a few other basic competencies. Language, which was chosen to be the intermediately objective section, included questions covering basic vocabulary, spelling, synonyms, antonyms, basic reading comprehension and so forth. Finally, the art section was designed to be the most subjective. In this section, we asked the children to draw a picture of their family doing their favorite activity and then to explain the activity.

[11] As the tests were equally likely to be assigned the characteristics described, any negative or positive effects of being assigned particular characteristics should be equal across individual tests, making the overall average a fair assessment of student performance.

We normalized the exam scores of each section and the overall total scores in the analysis that follows in order to facilitate comparisons with other studies in the literature. To do so, we pooled all of the grades assigned to each test copy by the teachers, and for each exam, subtracted the overall mean and divided by the standard deviation of the scores. Each section and the overall exam score are normalized relative to the distribution of the individual scores for the respective measure.[12]

In addition to the test data, we have data from the two surveys we administered. First, we have data from a survey of the children's parents that was conducted in order to collect information on the socio-demographic background of the children. Most importantly for the experiment, this included information on the family's caste, the age of the child, and the child's gender. Second, we have data from the teacher survey, which included basic demographic information as well as questions regarding the types of students that the teachers normally teach. The demographic information included the teachers' religion, caste, the type of school at which they taught (public or private), their 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 teachers' responses to these questions – all of the teachers taught low income students like those in our sample, either in a local public or private school.

C. Empirical Strategy to Measure Discrimination

The random assignment of tests to teachers and of children's characteristics to the coversheets should ensure that there is no systematic correlation between the quality of the graded tests, the

[12] In results not presented in this paper, we have also estimated the results normalizing relative to the distribution of blind test scores. Since this is a linear transformation of the dependent variable, it does not affect the hypothesis tests, but we still obtain estimates of similar magnitude.

characteristics of the grader, and the characteristics on the coversheet. We check this assumption using the following model:

$$z_{ij} = \beta v_{ij} + \varepsilon_{ij} \quad (1)$$

In this equation, z_{ij} is the original characteristics of the child who provided exam i and was graded by teacher j. The variable 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, allowing us to contrast the treatment of children in the lower caste groups to that of the high caste group.[13]

Using a model similar to Equation 1, we can then estimate the effect of the assigned characteristics on teacher test scores:

$$y_{ij} = \beta v_{ij} + \varepsilon_{ij} \quad (2)$$

where the variable y_{ij} is the test score assigned to test i by the teacher j. While the random assignment eliminates the systematic correlation between the true child characteristics and those observed by the teachers, it is possible that small differences in the types of tests assigned to each category will exist in any finite sample. To ensure that our estimates are robust to these small differences, we estimated two additional specifications. First, we include a difference estimator that controls for child characteristics. The difference estimator takes the following form:

$$y_{ij} = \beta v_{ij} + \delta z_{ij} + \varepsilon_{ij} \quad (3)$$

where z_{ij} is a linear control function that includes the true characteristics of the child taking test i. Second, we include a fixed-effects estimator, which takes the following form:

[13] In the specification shown in Appendix Table 2, we use a series of indicator variables for the specific caste groups (Brahmin, Kshatriya, Vaishya, or Shudra) that were assigned.

$$y_{ij} = \beta v_{ij} + \delta z_{ij} + \tau_j w_j + \varepsilon_{ij} \tag{4}$$

where w_j is the grader fixed effects. This specification allows us to control for fixed differences in grading practices across teachers.

IV. DESCRIPTIVE STATISTICS AND INTERNAL VALIDITY

In this section, we first provide descriptive statistics on the characteristics of the children who sat for the exam and the teachers who graded it. Next, we explore whether the original characteristics of the child predicts the exam score. Finally, we provide a check on the randomization.

A. Descriptive Statistics

In Table 1, we provide descriptive statistics on the 120 teachers who participated in the exam competition. Panel A provides information on the demographic characteristics of the teachers, while Panel B provides sample statistics on their caste identity and beliefs. In Column 1, we provide the summary statistics for the full sample. In the subsequent columns, we disaggregate the data by their basic demographic characteristics: 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, and finally, we divide the sample by the teachers' education level in Columns 6 and 7.

Reflecting the fact that teaching (especially at a public school) is a well-paid and desirable occupation, sixty-eight percent of the teachers identify themselves as belonging to the upper caste group (Panel A, Column 1). Teachers tend to be relatively young (an average age of thirty-five) and female (seventy-three percent). We made a point to recruit at both public and private schools. The effort was successful in that we recruited a fairly equal number of teachers across the two groups into the sample. Forty-four percent of the teachers work in public schools, while fifty-six percent work in private schools. About half of the sample holds a master's degree.

As Panel B demonstrates, caste identity is high among the teachers. Sixty-four percent report that their closest friend is of the same caste group and forty-one percent report that they belong to a caste association. Interestingly, even the teachers themselves tend to report that they believe that "teachers favor some students over others in their grading for reasons unrelated to educational performance." Eighty-one percent of the teachers agreed with this statement.

Comparing the characteristics of teachers across Columns 2 through 7, the relationships between the various characteristics generally follow the expected patterns. Low caste teachers are more represented in the comparatively less desirable private school teaching positions, less likely to have a master's degree, more likely to be male and more likely to belong to a caste association (Columns 2 – 3). Female teachers tend to be high caste (75 percent for versus 48 percent for men) and are also more likely to have a master's degree (Columns 4 – 5). A somewhat surprising pattern lies in the relationship between education and beliefs (Panel B, Columns 6 – 7). We do not observe a difference in caste identity or beliefs across those with or without a master's degree.

In Table 2, we provide summary statistics for the children who participated in the exam competition. We describe the original characteristics of the children and the characteristics of the children observed by the teacher in Columns 1 and 2, respectively. Column 1 contains averages for the actual sixty-nine children, while Column 2 contains averages for the 3,000 exam copies graded by the teachers. Standard deviations are provided in parentheses below each average.

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. In our sample, 18 percent of the children originally belonged to the high caste group, while 12 percent of exams were assigned this characteristic. Despite an effort to recruit 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 twenty-five percent. In Panel C, we show the average age and gender of the children. The mean observed age of the children (10.95 years) is approximately the same as the mean age of the observed test characteristics (10.98 years). To maximize power, we elected to have equal sized gender groups, and therefore, there are more females in the observed sample (50 percent) as compared to the actual sample (44 percent).

Table 3 provides a description of the average quality of the tests taken by the children. Rather than the normalized scores used in the rest of our analysis, we provide the test scores measured as the fraction of total possible points, for easy interpretation. On average, students scored a total of 63 percent on the exam. Students scored the lowest in art (47 percent) and the highest in math (68 percent).

The data suggest that the grading of the exam's art section may have been more subjective than the grading of the math or language sections. 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). In addition, the variance on the math and language sections of the exams are almost equal at 0.22, 0.23 and 0.16 percentage points, respectively, on both the teacher and the blind test scores. On the other hand, the average art scores given by the teacher are much lower, with a mean of 47 percent for the teachers compared with 64 percent for the blind graders. Moreover, the larger variance for the art section (0.32 and 0.35) provides confirming evidence that, as intended, the art section may be more subjective than the other sections of the exam.

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. The score ranges per exam are quite large, particularly at the lower portion of the test quality distribution. This indicates that the teachers assign partial credit very differently.

Who won the exam competition? In reality, low caste females won both age categories. The two winning exams each displayed the low caste characteristics about 80 percent of the time. About half the time, the winning exams were assigned as female and the average age on the winning exams was eleven years old. Thus, the winning exam was, on average, assigned the mean characteristics in our sample, as we would predict given the randomization.

B. Do Actual Characteristics Predict Exam Scores?

In this section, we investigate the relationship between the actual characteristics of the children in our sample and their exam scores. In the first column of Table 4, we present the simple correlation between the total test scores that the teachers assigned to the exams and the true underlying characteristics of the children. In Column 2, we add the blind test score as an additional control. In Columns 3 – 5, we disaggregate the test scores by individual subjects. All scores have been normalized relative to the overall distribution of scores for each respective section.

The children's original demographic characteristics strongly predict the exam scores. 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 on the exam 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.

In Column 2, we replicate the specification in Column 1, adding the score that our blind grader awarded to each exam as an additional control variable. The blind score provides us with a measure of performance on the exam that reflects only the underlying quality of the exam. Any difference between the test scores from the teachers and the scores from the blind grading can be attributed partially to discrimination, but also to the natural variation in grading practices. The total blind score awarded to the test is highly correlated with the score that the teachers assigned to the tests. On average, a one standard deviation increase in the blind score results in a 0.93 standard deviations increase in the total test score. When we include the blind test score, the coefficients on the low caste and female indicator variables are closer to zero, but the age variable still is a significant predictor of the final score.

We next disaggregate the test score data by subject in Columns 3 through 5 of Table 4. The results suggest that the different sections of the exam do provide variation in subjectivity, with the art section being much more subjective than the other sections. The correlation between the blind score and the teacher's score for the math and language sections is the same as for the overall score (about 0.93). The art section, however, has a coefficient that is only 0.63. Even when including the blind test score, the original caste status significantly predicts the math and art scores and the child's original age still predicts the test scores in all three subjects.

[14]Appendix Table 1 replicates Table 4 while disaggregating by specific caste group. Recall that the caste groups, in terms of descending order of prestige, are the Brahmin, Kshatriya, Vaishya, and Shudra castes. Children who belong to Kshatriya caste perform worse (-0.16 standard deviations) than the students who belong to Brahman caste, which is the omitted category in the regressions (Column 1). Children from the Vaishya caste then score worse than the students from the Kshatriya caste by 0.36 standard deviations, and children who belong to the Shudra group score the worst (-1.17 standard deviations lower than the children from the Brahman caste).

C. Internal Validity

In order to determine whether discrimination exists, we must first confirm that the average characteristics assigned to each test during the randomization process are effectively the same. We can test for this in two ways. First, we can verify this by regressing the actual characteristics of the children on each exam on the characteristics assigned to the exams by the random assignment process (Table 5, Column 1 – 3). Second, we can regress the test scores from the blind grading of the exam on the characteristics assigned to the exams (Columns 4 – 7). For each specification, we present the coefficients on each observed characteristic, as well as the F-statistic from the joint hypothesis test of the statistical significance of all the observed characteristics. For convenience, we also provide the p-value of the joint test.

The results described in Table 5 demonstrate that the random assignment process succeeded in assigning characteristics to the cover sheets that are, on average, uncorrelated with the actual characteristics or performance of the children. With the exception of the fact that tests from actual females are more likely to be assigned a younger age, none of the other coefficients are significant. In terms of magnitude, all of the coefficients are practically small; almost every coefficient is less than 1/10 of a standard deviation. The joint tests provide further evidence that the assigned characteristics are uncorrelated with the actual exams. Of the seven estimated equations, none are statistically significant at the 10 percent level. In particular, as shown in Column 4, we find little correlation between all of the assigned characteristics and the quality of the exam, as measured by the blind test score (p-value of .64).[15]

[15] In Appendix Table 2, we disaggregate the exam data by individual caste group. The table further confirms that the randomization was successful, as the individual castes are uncorrelated with the actual characteristics and the blind test score.

V. DO TEACHERS DISCRIMINATE?

In Table 6, we present the results of the regression of the exam scores on observed caste, gender and age.[16] In Column 1, we provide the overall effects of the observed characteristics on the test scores assigned by the teachers (Equation 2). Given the randomization, we do not necessarily need to include control variables for the characteristics of the child and the teacher. However, doing so may provide us with greater precision. Therefore, in Column 2, we present the results of specifications in which we control for the actual child's baseline characteristics (Equation 3). In Column 3, we present the results of the specification that includes the grader fixed effect (Equation 4). As a robustness check, we also control for the blind test score in Column 4. The blind test score can be viewed as another measure of the underlying characteristics of the child who took the exam.

We first examine the results on caste. Looking at Column 1, we find that the teachers gave, on average, the exams assigned to be "low caste" scores that were 0.09 standard deviations lower than an exam that was assigned to be "high caste" (significant at the ten percent level).[17] 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

[16] In Appendix Table 3 (Column 1), we show the results by disaggregated caste groups. While observed gender and age are still included in the specification, the results are nearly identical to Table 6 and, therefore, we omit them from the tables for conciseness. All specifications also include the original test characteristics and grader fixed effects. Recall that the caste groups in terms of descending order of prestige are the Kshatriya, Vaishya, and Shudra. We find significant differences between the exams that were assigned to the high caste group and exams that were assigned to either the Kshatiya and Shudra groups; the effect on exams that were assigned to the Vaishya group, while negative, is not significant at conventional levels (significant at the 15% level). We cannot reject the hypothesis that the coefficients on the three observed caste variables are significantly different from one another.

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

five percent level. The addition of the blind test score causes the point estimate to fall to -0.027 (Column 4). The estimate, however, remains statistically significant at the ten percent level.

Our results suggest that while discrimination may be present, the magnitude of the overall effect is relatively small when compared to the actual differences in test scores across the caste groups. The caste gap due to discrimination from our preferred specification in Column 3 (including teacher fixed effects and original characteristics control variables) is -0.086, which is much smaller than the 0.41 standard deviation difference based on actual characteristics from Table 3. The effect size falls within the lower tail of the distribution of the impacts of various education interventions in the developing world that have been evaluated. Successful interventions have typically fallen within a 0.07 to 0.47 standard deviation range; this range includes evaluations of programs that provide additional teachers (Banerjee, Cole, Duflo, and Linden, 2007), teacher monitoring and incentive programs (Duflo, Hanna, and Ryan, 2010; Glewwe, Illias, and Kremer, 2003), tracking programs (Duflo, Dupas, and Kremer, 2008), scholarships for girls (Kremer, Miguel, and Thornton, 2009), and contract teachers (Muralidharan and Sundararaman, 2008).

Interestingly, we do not find any effect of assigned gender or age on total test scores, regardless of specification (Table 6).[18] Note that not only are the effects not statistically significant, but also the magnitudes of the effects are very small. For example, being labeled with an additional year of age provides between a 0.001 – 0.003 increase in score.[19]

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[18] 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. We had initially discussed whether we should reprint all the exams electronically to remove the handwriting effect, but we decided that this was too divorced from reality. Therefore, we cannot fully rule this out. However, the existing evidence suggests that this may not be too problematic. For example, Lavy (2008) finds that the bias against boys is the same in both subjects where girls can be more easily identified from their handwriting and those where it harder deduce gender from the handwriting.

[19] Like gender it is possible that the child's actual age is discernable from the exam. It's possible, for example, that a teacher might have received an exam from a young child that was assigned an older grade and not believed the assignment, perhaps ignoring age altogether as a result. The existing evidence goes against this theory.   While age

Finally, in Appendix Table 4, we show the results of specifications where we interact the low caste dummy variable with the female dummy variable. The layout of the table is the same as in Table 6. The sign of the interaction between low caste and female is positive, but the coefficient is indistinguishable from zero. Thus, we do not find any evidence that low caste girls are treated differently than low caste boys.

VI. THE NATURE OF DISCRIMINATION

In this section, we explore three primary theories of discrimination. In the first section, we explore whether teachers are exhibiting behaviors that are consistent with statistical or taste-based discrimination. Second, we explore whether the subjectivity of the exam influences the level of discrimination. Finally, we test for the presence of in-group bias.

A. Statistical versus Taste Based Discrimination

In this section, we test for behaviors that are consistent with the implications of both theories (please see the conceptual framework for an extended discussion). First, under taste-based discrimination, we would have no reason to expect that the level of discrimination would vary based on the order in which the exams are graded. If discrimination varies by the grading order of the exam, then this points towards against the presence of taste-based discrimination. Second, if teachers statistically discriminate due to laziness, then patterns of discrimination would be uncorrelated with the underlying quality of the exam. If we do observe a correlation,

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is a large and significant predictor of test score, the range of test scores for children is large. 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 7 year old (41). More generally, a national survey of children aged 7-14 in India showed that the range of skills of children in India vary significantly by age (Pratham, 2005).

then this may be evidence of taste-based discrimination or of a model of statistical discrimination that is based on priors regarding the variance of the exam.

Empirical Results

To understand whether discrimination is correlated with exam order, we randomly ordered the exams in the packet. Therefore, for each teacher, we know which exams were graded first (when there was more uncertainty about how to assign grades, and the teacher had less understanding of what the distribution would look like) and which exams were graded towards the end (when presumably the teachers had figured out how to grade the exam).

To begin, we graph the relationship between assigned scores and grading order by caste group (Figure 2A) and by gender (Figure 2B). The x-axis is the order in which the exams were graded (from 1 to 25). In Figure 2A, the dotted line signifies the assigned scores for the low caste group, while the straight line signifies this for the high caste group. We find a gap in test scores between the low and high caste groups at the start of the grading order, but this effect fades as the place in the grading order increases. Figure 2B looks at this effect for gender, where the dotted line signifies the assigned score for female and the straight lines signifies this for males. We observe that at the start of the grading process, tests that are assigned to be male tend to score higher than those that are assigned to be female. The effect quickly fades away for much of the the grading process, but at the very end, we observe the exams that are assigned to be females being graded slightly higher than those assigned to be males.

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 observed characteristics. In Column 2, we show the results of the interaction between the observed 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 and the grader fixed effects.

We find that the grading order matters. Independent of order, teachers mark exams that are assigned to be low caste 0.23 standard deviations lower (significant at the 5 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 0.12 standard deviation gap between the low and high caste exams (although this is only significant at about the 20 percent level) and a 0.10 gap between the exams that were assigned to be female and male (significant at the 1 percent level).

Next, we try to understand whether the underlying exam quality influences the teacher's actions. We begin by constructing a non-parametric estimate of the relationship between the score assigned to the exam and the score from the blind grading. The estimates are constructed using a local linear polynomial estimator (bandwidth of 0.4). In Figure 2A, the solid line represents the scores assigned to tests labeled as high caste and the dashed line represents the scores assigned to the tests labeled as lower caste. In Figure 2B, the dotted line signifies the assigned score for female tests and the straight lines signifies this for male tests. For the lowest quality exams (as measured by the blind test score), the high caste children are consistently scored higher than the lower caste children.[20] Low performing, low caste girls appear to be marked higher than low performing boys (although the effect appears very small).

[20] For caste, there is a clear break that emerges in the data at about -1.1 standard deviations, in which the high caste children are consistently scored higher than the lower caste children. To estimate this directly, we interact the lower

We test this more formally in Table 8. In Column 1, we interact the blind test score with the observed characteristics and control for the blind test score, using the following equation:

$$y_{ij} = \beta v_{ij} + \lambda q_i + \eta v_{ij} * q_i + \delta z_{ij} + \tau_j w_j + \varepsilon_{ij} \qquad (5)$$

where q_i is the blind test score for test *i*. Independent of the blind score, we find that the teachers grade low caste exams down by 0.029 standard deviations. However, possessing a higher quality exam mitigates this effect. Specifically, a one standard deviation increase in the blind test score leads to a 0.03 standard deviation increase in the difference between the low caste and high caste groups (statistically significant at the ten percent level).

We next create an indicator variable for whether an exam is of high or low quality (Column 2). The variable equals one if the blind test score is above average and equals zero otherwise. We then estimate a specification that includes the interactions of this variable with each of the assigned demographic characteristics. We find that teachers grade the below average exams that were assigned to be low caste down by -0.108 standard deviations (statistically significant at the 5 percent level). The effect then disappears for high quality exams with a difference in scores of only -0.025 standard deviations. It is important, however, to note that the difference in the effect on low scoring tests versus high scoring tests (0.083 standard deviations) is only statistically significant at the 20 percent level. Thus, there is some evidence that teachers hurt low caste children that match perceived stereotypes. Interestingly, we also see that teachers grade low quality exams that were assigned to be female up by 0.107 standard deviations (significant at the 1 percent level), but then again the difference disappears for high quality

caste indicator with an indicator for having a blindly graded score below -1.1 standard deviations (results available on request). Consistent with Figure 2A, lower caste children with a blind test score below -1.1 standard deviations score, on average, -0.15 standard deviations lower than their high caste peers (statistically significant at the 1 percent level).

exams (the difference in the effect of gender between high and low quality exams is significant at the 1 percent level).

Finally, in Column 3, we explore whether being randomly assigned very few high performing, low caste kids at the start of the grading process (during the first five exams) affects how the teachers grade the rest of the children (the remaining 20 exams). Those who had few "high performing, low caste" papers grade low caste students 0.167 higher than their equivalent high caste peers, but this difference is not significant at conventional levels (p-value of 0.11).[21] However, note that by splitting the sample in the manner, we reduce the sample size from 3,000 to 2,400 exams, and therefore, have less statistical power.

Discussion

In sum, the data suggest two facts. First, the teachers discriminate more at the start of the exam and this effect fades over time. Second, the level of discrimination is dependent on the underlying quality of the exam. Do these facts imply statistical or taste-based discrimination?

Given that teachers use the underlying quality of the exam while discriminating, we might take this to be evidence of taste-based discrimination. However, under this model, there is no reason to expect that discrimination would vary based on the grading order, which we find to be the case.

Therefore, is the evidence consistent with statistical discrimination instead? Teachers may statistically discriminate in two ways. First, teachers may be lazy and use statistical discrimination to reduce the amount of time they need to spend grading each exam. While we

[21] In regressions not reported here, we also explore whether teachers treated low quality exams from low caste students differently from high quality exams if the teachers were assigned very few high performing, low caste children at the start. We do not observe any significant differences. The tables are available from the authors upon request.

cannot fully rule out this story, 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 slacking.

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. For example, if they observe a low caste exam of low quality, they may expect that the exam is even lower quality than observed. The two facts documented above would be consistent with this story, as teachers would take both the quality of the exam and the order of the exam into account.

However, 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.[22] 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, we observe discrimination based on caste and gender, but not age.

[22] Farmer and Terrell (1996) provide a theoretical extension of the basic statistical discrimination model that shows how inaccurate initial assessments of a group can generate self-fulfilling prophecies, where group members have incentives to live up to the low expectations that have been set for them.

Thus, if they are statistically discriminating, then the teachers might have incomplete information, might just be bad at making 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.[23]

B. 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.[24] As demonstrated in Table 2, the relative subjectivity of these sections is borne out by the significantly lower correlations between blind and non-blind scores on the exam's art section relative to the other sections. In Table 9, we present the results disaggregated by subject. All specifications include the original test characteristics and grader fixed effects as controls. Interestingly, we do not see significant differences across the three subjects. Even in the art section, the observed reduction in test scores for lower caste students is similar to the estimates for 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 for each question. Despite the fact that the questions on the test were relatively simple, the graders still

[23] Of course, it is important to note that 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 the full year.

[24] 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.

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, all the exams provided the teachers with some level of discretion.

C. In-Group Bias

Finally, we explore whether teachers differ in the degree to which they use students' observed characteristics as proxies for actual performance. Specifically, as discussed in Section II, many claim that individuals discriminate in favor of their own group (in-group bias). We explore this in the context of caste and gender. In addition, we estimate whether the degree of discrimination varies by teachers' education levels or age, since much of the education literature suggests that these characteristics may also influence the level of discrimination. Specifically, the literature suggests that 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 10. 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 difference between the coefficients. In Column 4, we present results of a specification that includes the interactions between the observed caste variables and all four teacher demographic variables. All regressions include both original test characteristics and grader fixed effects.

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 0.2 standard deviations—and significant at the 5 percent level (Column 3).[25] Of course, as described in Table 1, lower caste teachers tend to come from a different socio-economic background than upper caste teachers (more likely to be male, less likely to have a master's degree, etc), and these characteristics, not caste, may account for the results we find. To control for these possible confounds, in Column 4, we control for both the main characteristics and the interactions of the characteristics with the observed low caste status. The results remain the same: lower caste teachers significantly downgrade exams that are assigned to be lower caste, relative to the high caste teachers.

Turning to gender, we also do not observe in-group bias. We do not see a significant difference in the way female and male teachers grade exams that are randomly assigned to be male versus female. In terms of caste, 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, while 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 estimates.

While we find no significant difference in caste discrimination by teachers' education or age, we find that more educated teachers and older teachers are more likely to give higher grades to exams that were assigned to be female.

[25] Of course, the level of "in-group" bias may vary based the quality of the underlying exam. Appendix Table 5 sheds light on this, by providing evidence on the interaction between observed caste and the blind test score for each group of teachers. Low caste teachers do grade the low quality, low caste exams lower than the low quality high caste exams, while grading high quality, low caste exams the same as high quality, high caste ones (Column 3 and 4). While this pattern also holds for the high caste teachers, the coefficients cannot always be rejected from zero (Columns 1 and 2).

VII. 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 teachers 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 0.09 standard deviations higher than those assigned to be lower caste. We do not find any overall evidence of discrimination by gender. Disaggregating the results by the quality of the exam, the low-performing low caste children lose out due to discrimination, while low-performing females appear to be given an advantage. The evidence suggests that teachers appear to 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 teachers are practicing statistical discrimination when there is more uncertainty over the testing instrument. This could imply that policies designed to increase teachers' understanding of an exam may reduce discrimination. Future research should try to determine whether improving teacher confidence and quality through training programs reduces discrimination. Second, teachers naturally added subjectivity to "objective" subjects like math through the generous use of partial credit. It would be important to further understand how teachers assign partial credit and whether helping teachers learn 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. Future research should aim to understand how experiments such as this can be modified to incorporate other methods through which teachers may convey biases.

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Table 1: Characteristics of the Teachers

Characteristic	All (1)	Caste: High Caste (2)	Caste: Low Caste (3)	Gender: Female (4)	Gender: Male (5)	Education: No Master's (6)	Education: Master's (7)
Number of teachers	120	81	39	87	33	61	59
A. Teacher Characteristics							
Upper 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
B. Teacher Beliefs							
Closest Friend: Same Caste Grouping	0.64	0.74	0.44	0.72	0.42	0.66	0.63
Belong to a Caste Association	0.41	0.39	0.46	0.44	0.33	0.42	0.41
Believe that "teachers favor some students over others in their grading for reasons unrelated to their educational performance."	0.81	0.83	0.77	0.82	0.79	0.80	0.81

Notes:

1. This table summarizes the characteristics and beliefs of the 120 teachers who participated in the grading sessions.

Table 2: Child Characteristics

	Original (1)	Observed (2)
A. High Caste		
Brahmin	0.18	0.12
	(0.39)	(0.33)
B. Lower 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)	
C. Other		
Female	0.44	0.50
	(0.50)	(0.50)
Age	10.95	10.98
	(2.04)	(2.00)

Notes:

1. This table summarizes both the real characteristics of the children in our sample and the characteristics observed by the teachers.

2. The original (true) characteristics, listed in Column 1, include data on all 69 children who completed a test and a demographic survey.

3. Column 2 provides data on the characteristics that were randomly assigned to the cover sheets of the tests that the teachers graded. This column summarizes the data from the 3,000 coversheets in the study (25 for each of 120 teachers).

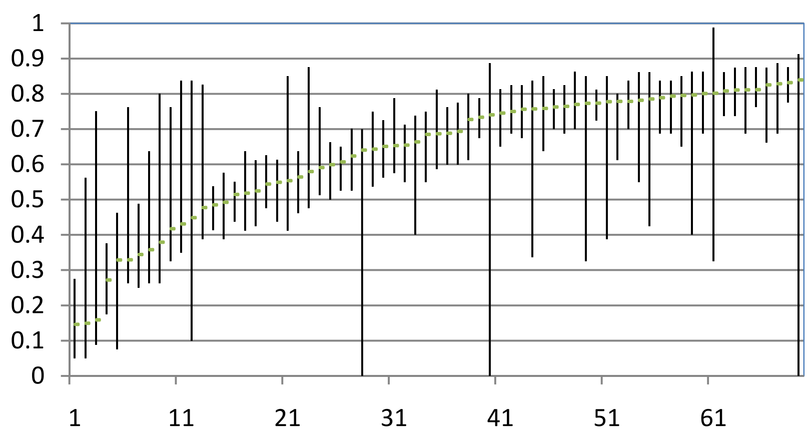
Table 3: Description of Test Scores

	Teacher Scores	Blind Test Score
	(1)	(2)
A. Test Score		
Total	0.63	0.67
	(0.19)	(0.19)
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	3000	69

Notes:

1. This table summarizes the test scores from the exam tournament. The scores are presented in terms of the percentage of total possible points.
2. 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:

1. Figure 1 provides the range of test scores (in percentages) given by the teachers for each of the 69 exams used in the study.

Table 4: Correlations between Original Characteristics and Final Test Scores

Test Type:	Total	Total	Math	Hindi	Art
	(1)	(2)	(3)	(4)	(5)
Constant	-5.348	-0.927	-0.941	-0.97	-1.094
	(0.416)***	(0.164)***	(0.169)***	(0.191)***	(0.330)***
Low Caste	-0.409	-0.013	-0.026	0.008	-0.111
	(0.037)***	(0.014)	(0.015)*	(0.017)	(0.029)***
Female	0.183	-0.011	0.006	-0.001	0.004
	(0.029)***	(0.011)	(0.012)	(0.013)	(0.023)
Age	0.846	0.142	0.164	0.133	0.147
	(0.079)***	(0.031)***	(0.032)***	(0.036)***	(0.062)**
Age^2	-0.03	-0.006	-0.007	-0.005	-0.007
	(0.004)***	(0.001)***	(0.001)***	(0.002)***	(0.003)**
Blind Test Score		0.926	0.929	0.932	0.634
		(0.007)***	(0.007)***	(0.008)***	(0.014)***
Observations	3000	3000	3000	3000	3000
R-squared	0.28	0.89	0.9	0.85	0.5

Notes:

1. This table contains the raw correlations between the grades awarded to the exams by teachers and the children's original, unobserved characteristics.

2. The first two columns contain results for the total test score, with and without controlling for the blind test score. Columns 3 - 5 present the results, controlling for the blind test score, by exam section.

3. Child performance on each exam is measured using the score normalized to the overall exam score distribution.

4. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Table 5: Randomization Check

	Actual Characteristics			Blind Scores			
	Low Caste	Female	Age	Total	Math	Hindi	Art
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low Caste	-0.035	0.006	-0.071	-0.068	-0.062	-0.064	-0.054
	(0.021)	(0.027)	(0.113)	(0.054)	(0.055)	(0.054)	(0.055)
Female	-0.02	-0.022	-0.022	0.012	0.031	-0.001	-0.02
	(0.014)	(0.018)	(0.075)	(0.036)	(0.036)	(0.036)	(0.036)
Age	-0.063	-0.100	0.053	-0.014	0.045	-0.076	-0.007
	(0.045)	(0.058)*	(0.237)	(0.114)	(0.115)	(0.114)	(0.115)
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	3000	3000	3000	3000	3000	3000	3000
F-Stat	1.85	1.17	0.25	0.43	0.64	0.48	0.89
P-Value	0.1157	0.3215	0.9082	0.7889	0.6358	0.7501	0.4682

Notes:

1. 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.

2. The F-statistic and p-value provide the results of a test of joint significance of the observed characteristics.

3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Table 6: Effect of Observed Characteristics on Total Test Scores

Observed Characteristics	(1)	(2)	(3)	(4)
Low Caste	-0.09	-0.087	-0.086	-0.027
	(0.054)*	(0.044)**	(0.043)**	(0.017)*
Female	0.022	0.015	0.014	0.008
	(0.036)	(0.029)	(0.029)	(0.011)
Age	0.001	0.003	0.003	0.001
	(0.009)	(0.007)	(0.007)	(0.003)
Original Test Characteristics		YES	YES	YES
Grader Fixed Effect			YES	YES
Blind Test Score				YES

Notes:

1. This table presents the regression of total normalized test scores on observed characteristics that were randomly assigned to the coversheets of test copies.

2. The sample includes the 3,000 graded exams (graded in sets of 25 by 120 teachers).

3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Figure 2A: The Caste Gap, by Grading Order

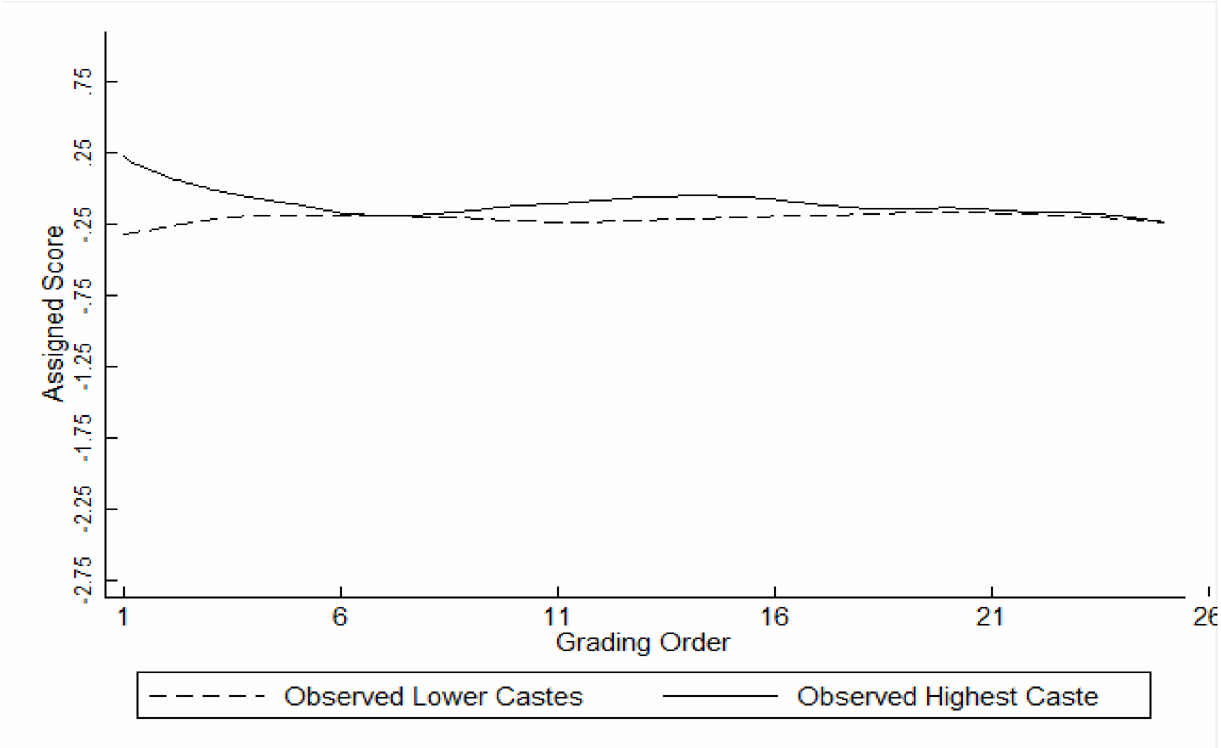
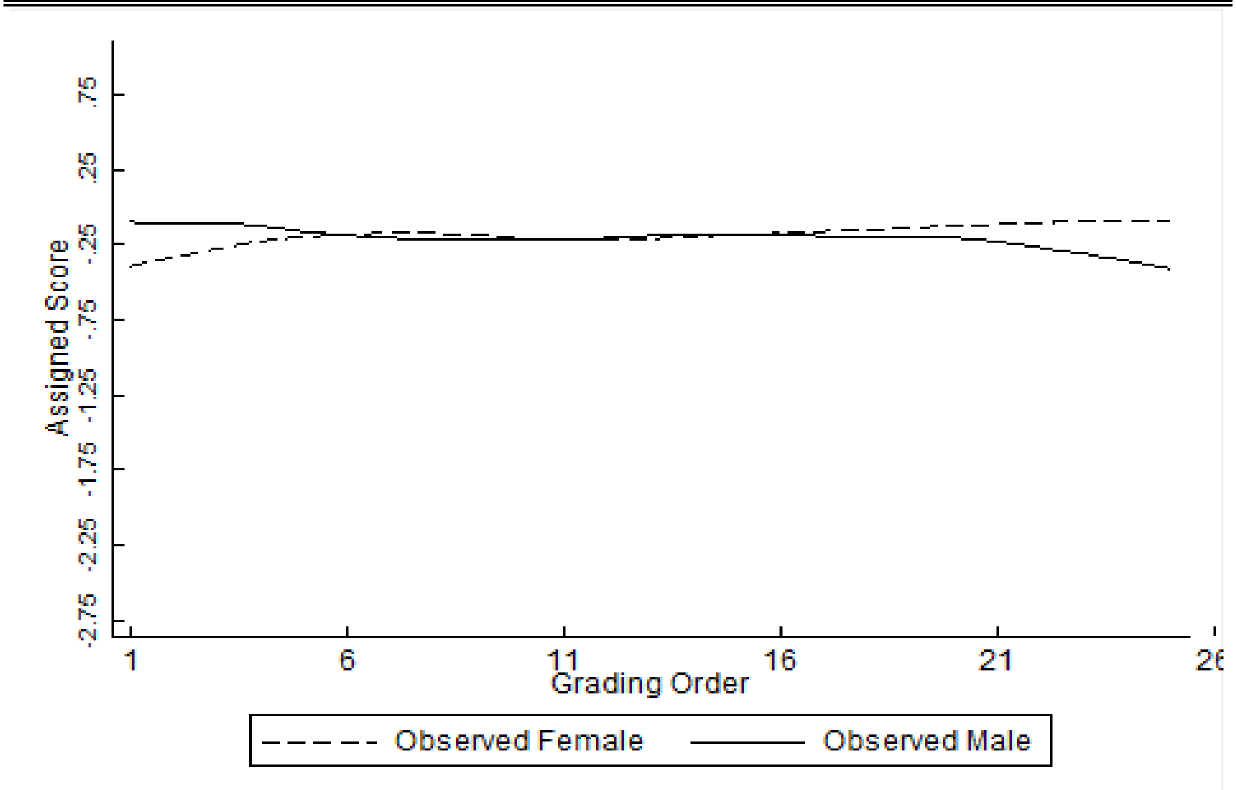


Figure 2B: The Gender Gap, by Grading Order



Notes:

1. Figure estimates the relationship between the normalized total score and the order in which the exams were graded.
2. Relationship estimated using a local linear polynomial estimate with an Epanechnikov kernal and a bandwidth of 5.

Table 7: Effect on Test Scores, by Grading Order

Observed Characteristics	(1)	(2)
Constant	-5.657	-5.872
	(0.500)***	(0.479)***
Low Caste	-0.233	-0.03
	(0.093)**	(0.058)
Female	-0.098	0.063
	(0.060)	(0.040)
Age	0.004	-0.002
	(0.015)	(0.010)
Low Caste * Grading Order	0.011	
	(0.006)*	
Female * Grading Order	0.009	
	(0.004)**	
Age * Grading Order	0.000	
	(0.001)	
Grading Order	-0.014	
	(0.013)	
Low Caste * Start of Grading Order		-0.120
		(0.089)
Female * Start of Grading Order		-0.102
		(0.058)*
Age* Start of Grading Order		0.01
		(0.015)
Start of Grading Order		0.035
		(0.184)
Original Test Characteristics	YES	YES
Grader Fixed Effect	YES	YES

Notes:

1. This table explores whether the order in which the exam was graded affects the treatment of exams assigned to different observable characteristics.

2. The variable "grading order" is the order in which the teachers graded the exams. This variable ranges from 1 (1^{st} 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.

3. The outcome variable is the total normalized total score.

4. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).

5. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Figure 3A: The Caste Gap, by Blind Test Score

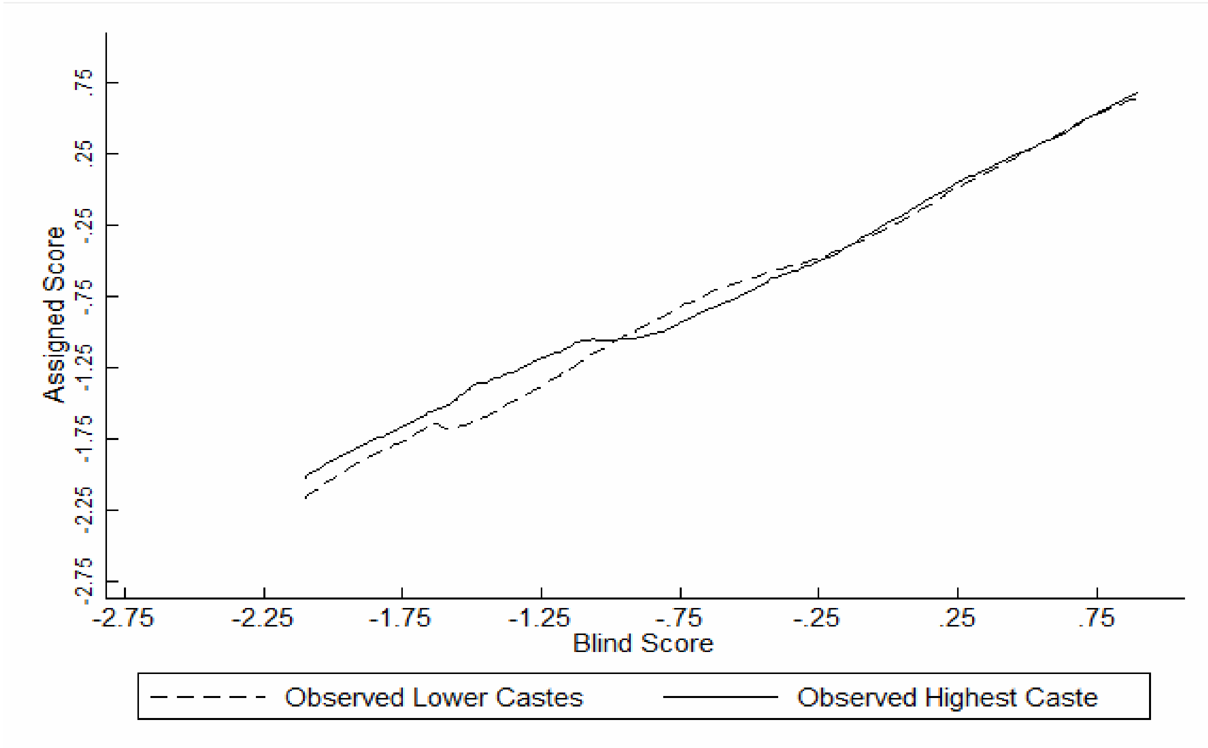
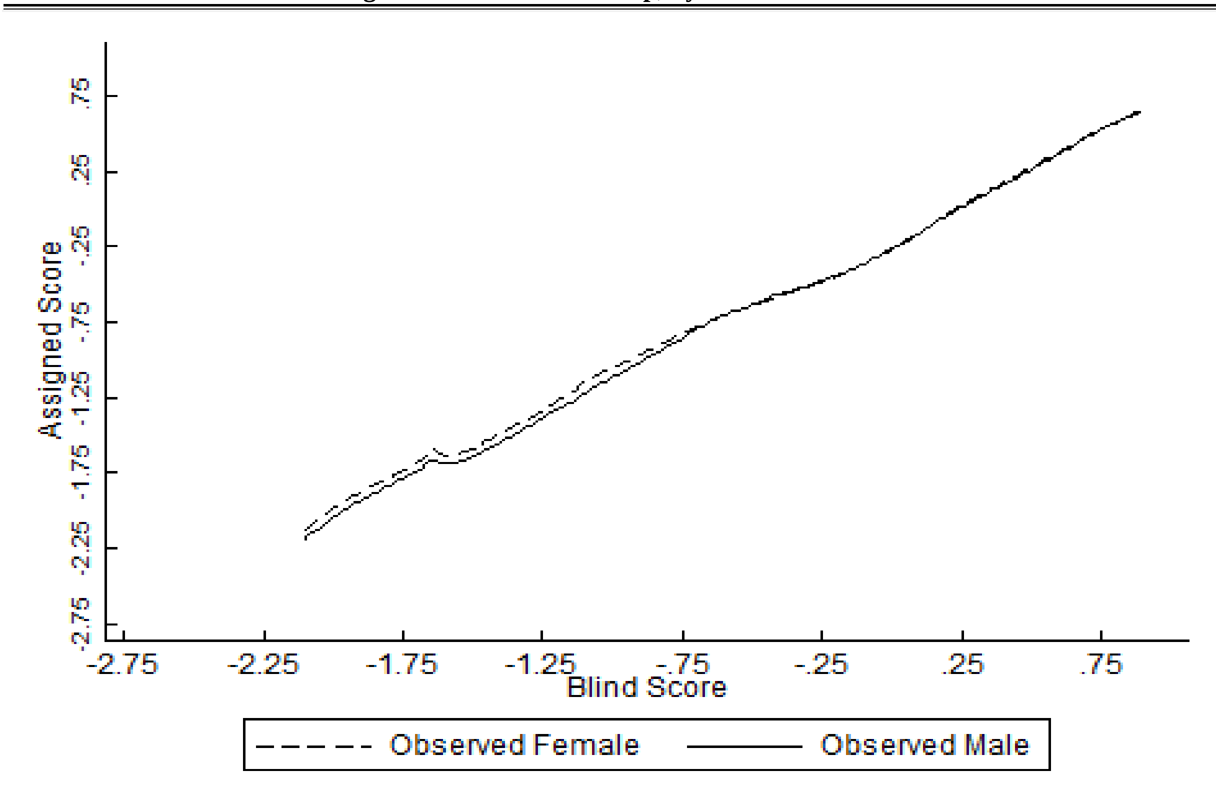


Figure 3B: The Gender Gap, by Blind Test Score



Notes:

1. Figure estimates the relationship between the normalized teacher assigned total score and the normalized blind score.
2. Relationship estimated using a local linear polynomial estimate with an Epanechnikov kernal and a bandwidth of 0.4.

Table 8: Effect on Test Scores, by Exam Quality

Observed Characteristics	(1)	(2)	(3)
Constant	-1.175	-3.264	-5.309
	(0.185)***	(0.328)***	(0.526)***
Low Caste	-0.029	-0.108	-0.095
	(0.017)*	(0.049)**	(0.058)
Female	0.008	0.107	0.048
	(0.011)	(0.032)***	(0.032)
Age	0.001	0.000	0.002
	(0.003)	(0.008)	(0.008)
Low Caste * Blind Test Score	0.03		
	(0.018)*		
Female * Blind Test Score	-0.015		
	(0.011)		
Age * Blind Test Score	-0.002		
	(0.003)		
Blind Test Score	0.921		
	(0.036)***		
Low Caste * Above Average Blind Score		0.083	
		(0.062)	
Female * Above Average Blind Score		-0.11	
		(0.040)***	
Age* Above Average Blind Score		-0.004	
		(0.010)	
Above Average		1.508	
		(0.128)***	
Low Caste * Had Few High Scoring Low Caste Papers at Start			0.167
			(0.104)
N	3000	3000	2400
Original Test Characteristics	YES	YES	YES
Grader Fixed Effect	YES	YES	YES

Notes:

1. This table explores whether discrimination varies by exam quality.

2. The outcome variable is the total normalized test score.

3. In Column 1, we interact the observed characteristics with the blind test score. We interact the observed characteristics with an indicator for above average blind score in Column 2. In Column 3, we interact caste with whether the teacher was radomly assigned few high scoring papers at the start.

4. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Table 9: Effect on Test Scores, by Subject

	Math	Hindi	Art
	(1)	(2)	(3)
Low Caste	-0.072	-0.08	-0.058
	(0.043)*	(0.047)*	(0.042)
Female	0.024	-0.004	0.011
	(0.029)	(0.031)	(0.028)
Age	0.007	0.001	-0.005
	(0.007)	(0.008)	(0.007)
Original Test Characteristics	YES	YES	YES
Grader Fixed Effect	YES	YES	YES

Notes:

1. This table presents the regression of normalized test scores for the indicated sections of the exam on the observed characteristics that were randomly assigned to the coversheets.

2. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).

3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Table 10: Effect on Test Scores, by Teacher Type

	Belongs to panel title category?			Difference (Conditional on other teacher characteristics)
	Yes	No	Difference	
	(1)	(2)	(3)	(4)
		A. Upper Caste		
Low Caste	-0.023	-0.227	0.197	0.204
	(0.052)	(0.078)***	(0.093)**	(0.098)**
Female	-0.01	0.059	-0.071	-0.058
	(0.035)	(0.051)	(0.061)	(0.065)
Age	0	0.008	-0.008	-0.01
	(0.009)	(0.013)	(0.015)	(0.016)
		B. Male		
Low Caste	-0.064	-0.094	0.031	0.105
	(0.084)	(0.051)*	(0.097)	(0.103)
Female	0.049	-0.001	0.056	0.03
	(0.055)	(0.034)	(0.064)	(0.068)
Age	0.009	0.001	0.008	0.007
	(0.014)	(0.008)	(0.016)	(0.017)
		C. Masters Degree		
Low Caste	-0.079	-0.09	0.011	-0.028
	(0.062)	(0.061)	(0.087)	(0.089)
Female	0.061	-0.033	0.093	0.127
	(0.041)	(0.040)	(0.057)	(0.059)**
Age	0.003	0.004	0	0.001
	(0.010)	(0.010)	(0.014)	(0.015)
		D. Below Median Age		
Low Caste	-0.135	-0.038	-0.099	-0.084
	(0.061)**	(0.062)	(0.087)	(0.092)
Female	0.061	-0.038	0.098	0.103
	(0.040)	(0.041)	(0.057)*	(0.061)*
Age	0	0.007	-0.007	-0.009
	(0.010)	(0.010)	(0.014)	(0.015)
Original Test Characteristics	YES	YES	YES	YES
Grader Fixed Effect	YES	YES	YES	YES

Notes:

1. This table presents estimates of discrimination disaggregated by the characteristics of the teachers.

2. Each panel contains four sets of estimates. 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. Column 4 presents the same interaction but from a specification that includes interactions with the teacher characteristics from all of the panels.

3. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).

4. The outcome in every regression is the normalized total score.

5. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Appendix Table 1: Correlations between Original Characteristics and Final Test Scores

	Total	Total	Math	Hindi	Art
	(6)	(7)	(8)	(9)	(10)
Constant	-4.928	-0.929	-0.874	-1.021	-1.054
	(0.403)***	(0.165)***	(0.171)***	(0.193)***	(0.333)***
Kshatriya	-0.161	-0.012	0	-0.01	-0.083
	(0.042)***	(0.017)	(0.018)	(0.020)	(0.034)**
Vaishya	-0.516	-0.016	-0.033	0.003	-0.127
	(0.039)***	(0.016)	(0.017)**	(0.019)	(0.033)***
Shudra	-1.171	-0.012	-0.03	0.042	-0.176
	(0.068)***	(0.029)	(0.030)	(0.033)	(0.055)***
Unknown	-0.336	-0.009	-0.049	0.036	-0.106
	(0.045)***	(0.018)	(0.019)**	(0.021)*	(0.037)***
Female	0.213	-0.012	0.003	-0.002	0.007
	(0.028)***	(0.012)	(0.012)	(0.014)	(0.024)
Age	0.781	0.142	0.151	0.143	0.139
	(0.076)***	(0.031)***	(0.032)***	(0.037)***	(0.063)**
Age^2	-0.027	-0.006	-0.007	-0.006	-0.006
	(0.004)***	(0.001)***	(0.001)***	(0.002)***	(0.003)**
Blind Test Score		0.926	0.926	0.935	0.631
		(0.007)***	(0.007)***	(0.009)***	(0.014)***
Observations	3000	3000	3000	3000	3000
R-squared	0.34	0.89	0.9	0.85	0.5

Notes:

1. This table contains the raw correlations between the grades awarded to the exams by teachers and the children's original, unobserved characteristics.
2. The first two columns contain results for the total test score, with and without controlling for the blind test score. Columns 3 - 5 present the results, controlling for the blind test score, by exam section.
3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Appendix Table 2: Randomization Check with Full Set of Caste Variables

	Actual Characteristics							Blind Scores			
	Brahmin	Kshatriya	Vaishya	Shudra	Unknown	Female	Age	Total	Math	Hindi	Art
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Kshatriya	0.041	-0.004	-0.039	0.024	-0.023	0.038	-0.199	-0.106	-0.093	-0.111	-0.062
	(0.028)	(0.032)	(0.035)	(0.017)	(0.028)	(0.036)	(0.150)	(0.072)	(0.072)	(0.072)	(0.072)
Vaishya	0.039	-0.026	-0.041	0.016	0.012	0.001	-0.079	-0.059	-0.056	-0.057	-0.035
	(0.022)*	(0.025)	(0.027)	(0.013)	(0.022)	(0.029)	(0.118)	(0.057)	(0.057)	(0.057)	(0.057)
Shudra	0.024	-0.027	0.009	0.007	-0.013	-0.001	0.01	-0.068	-0.061	-0.056	-0.087
	(0.025)	(0.027)	(0.030)	(0.015)	(0.024)	(0.031)	(0.129)	(0.063)	(0.063)	(0.062)	(0.063)
Female	0.02	-0.01	0.006	-0.009	-0.007	-0.021	-0.026	0.011	0.03	-0.002	-0.02
	(0.014)	(0.016)	(0.017)	(0.008)	(0.014)	(0.018)	(0.075)	(0.036)	(0.036)	(0.036)	(0.036)
Age	0.063	-0.034	0.053	-0.032	-0.05	-0.101	0.055	-0.013	0.046	-0.074	-0.005
	(0.045)	(0.050)	(0.055)	(0.027)	(0.045)	(0.058)*	(0.237)	(0.115)	(0.115)	(0.114)	(0.115)
Age^2	-0.003	0.002	-0.002	0.001	0.002	0.004	-0.003	0.001	-0.002	0.003	0
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)*	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000
F-Stat	1.38	0.47	1.41	1.06	0.95	1.08	0.61	0.4	0.5	0.48	0.83
P-Value	0.2184	0.8309	0.2084	0.3839	0.4613	0.3723	0.7212	0.8798	0.8106	0.8239	0.5469

Notes:

1. This table contains regressions of the actual characteristics of the children on the characteristics randomly assigned to the coversheet of the exam that was graded by the teachers.

2. The F-statistic and p-value provide the results of a test of joint significance of the observed characteristics.

3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Appendix Table 3: Effect of Detailed Caste Groups on Total Test Scores

Observed Characteristics	(1)	(2)	(3)
Constant	-5.892	-1.18	-3.275
	(0.471)***	(0.185)***	(0.328)***
Kshatriya	-0.112	-0.03	-0.206
	(0.057)*	(0.022)	(0.065)***
Vaishya	-0.067	-0.023	-0.083
	(0.045)	(0.017)	(0.051)
Shudra	-0.112	-0.042	-0.114
	(0.050)**	(0.019)**	(0.056)**
Kshatriya * Blind Test Score		0.028	
		(0.023)	
Vaishya * Blind Test Score		0.029	
		(0.018)	
Shudra * Blind Test Score		0.033	
		(0.020)	
Blind Test Score		0.92	
		(0.037)***	
Kshatriya * Above Average Blind			0.187
			(0.082)**
Vaishya * Above Average Blind			0.06
			(0.065)
Shudra * Above Average Blind			0.081
			(0.071)
Above Average			1.495
			(0.128)***
Original Test Characteristics	YES	YES	YES
Grader Fixed Effect	YES	YES	YES

Notes:

1. This table presents estimates of the effect of observed caste disaggregated by specific caste.

2. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).

3. The outcome variable in all regressions is the normalized total score.

4. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Appendix Table 4: Interaction of Gender and Caste

Observed Characteristics	(1)	(2)	(3)	(4)
Low Caste * Female	0.039	0.032	0.031	0.012
	(0.108)	(0.087)	(0.089)	(0.034)
Low Caste	-0.109	-0.103	-0.102	-0.033
	(0.076)	(0.061)*	(0.062)*	(0.024)
Female	-0.012	-0.013	-0.013	-0.002
	(0.101)	(0.081)	(0.083)	(0.032)
Age	0.001	0.003	0.003	0.001
	(0.009)	(0.007)	(0.007)	(0.003)
Original Test Characteristics		YES	YES	YES
Grader Fixed Effect			YES	YES
Blind Test Score				YES

Notes:

1. This table presents the regression of total normalized test scores on observed characteristics that were randomly assigned to the coversheets of test copies.

2. The sample includes the 3,000 graded exams (graded in sets of 25 by 120 teachers).

3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Appendix Table 5: Interaction of Low Caste with Blind Test Score

	Upper Caste		Low Caste	
	(1)	(2)	(3)	(4)
Low Caste * Blind Test Score	0.027		0.056	
	(0.015)*		(0.049)	
Low Caste	-0.012	-0.057	-0.08	-0.304
	(0.015)	(0.054)	(0.043)*	(0.113)***
Low Caste * Above Average Blind Score		0.019		0.289
		(0.070)		(0.133)**

Notes:

1. This table explores whether discrimination varies by exam quality and the caste of the teacher.

2. The outcome variable is the total normalized test score.

3. In Columns 1 and 3, we interact the observed characteristics with the blind test score, while we interact the observed characteristics with an indicator for above average blind score in Columns 3 and

4. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Measuring Discrimination in Education

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Abstract:

In this paper, we illustrate a methodology to measure discrimination in educational contexts. In India, we ran an exam competition through which children compete for a large financial prize. We recruited teachers to grade the exams. We then randomly assigned child "characteristics" (age, gender, and caste) to the cover sheets of the exams to ensure that there is no systematic relationship between the characteristics observed by the teachers and the quality of the exams. We find that teachers give exams that are assigned to be lower caste scores that are about 0.03 to 0.09 standard deviations lower than exams that are assigned to be high caste. The effect is small relative to the real differences in scores between the high and lower caste children. Low-performing, low caste children and top-performing females tend to lose out the most due to discrimination. Interestingly, we find that the discrimination against low caste students is driven by low caste teachers, while teachers who belong to higher caste groups do not appear to discriminate at all. This result runs counter to the previous literature, which tends to find that individuals discriminate in favor of members of their own groups.

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I. Introduction

Teachers' expectations seem to affect students' behavior. Numerous studies have documented what is known as the Pygmalion effect, through which students perform better (or worse) simply because they are expected to do so. For example, the seminal paper in the literature, Rosenthal and Jacobson (1968), has shown that individual students outperformed other students in school after their teachers were told at the start of the school year that they had excelled on a standardized test (even though they were randomly picked as "excelling"). Although this effect has been well documented, we do not yet understand the factors that teachers use to formulate prior opinions about students' abilities. Of particular concern is whether or not teachers base their beliefs on students' affiliations with a minority group. If this type of discrimination does exist, it can have long lasting effects, both reinforcing erroneous beliefs of inferiority (Steele and Aronson 1995, 1998; Hoff and Pandey, 2006) and discouraging children from making human capital investments (Mechtenberg, 2008; Taijel, 1970; Arrow 1972; Coate and Loury, 1993). Discrimination would, thus, hinder the effectiveness of education in leveling the playing field across children from different backgrounds.

Unfortunately, it is difficult to empirically test whether discrimination exists in the classroom. By definition, children from disadvantaged backgrounds exhibit many characteristics that are associated with poor academic performance—few educational resources in schools, low levels of parental education, families with little human or social capital, and even high rates of child labor. Thus, it is hard to understand whether children who belong to these minority groups perform worse in school, on average, due to discrimination or due to these other characteristics that may be associated with a disadvantaged background. 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."

We address this question through an experiment built around a prize exam competition. The method we illustrate can be used to measure discrimination in many educational contexts and locations; however, we demonstrate it in the Indian context, where discrimination based on caste is a potentially serious problem. Specifically, we designed an exam competition in which we recruited children to compete for a large financial prize. We, then, recruited local teachers and provided each teacher with a set of exams. We randomly assigned child "characteristics" (age, gender, and caste) to the cover sheets of the individual exams graded by the teachers to ensure that there would be no systematic relationship between the characteristics observed by the teachers and the quality of the exams.

This design has several key advantages. First, the random assignment allows us to overcome one of the major obstacles in measuring discrimination. Specifically, we can attribute any differences in the exam scores across different types of children to discrimination and not to other characteristics associated with belonging to a disadvantaged group. Second, the richness of the data available in the experiment allows us to investigate the structure of the observed discrimination and to understand how teachers discriminate, when they discriminate, and against which types of students.

Within the education literature, our work is closely related to a rich body of work in the United States that uses laboratory experiments to evaluate teachers' perceptions of African American students relative to Caucasian students. While the employed techniques range from evaluations of actual tests to video tapes of student performance and to measurements of teachers reactions to different students (see Furgeson (2003) for a thorough literature review), the basic strategy is to hold students' performance constant while varying the race of the student so that any variation in the experimental subjects' reaction to the student is due only to the students' race. Most of these studies find evidence of lower expectations of the performance of African American students and evidence of discrimination in evaluations. Our work is also very much also related to Lavy (2004), which uses a natural experiment to measure discrimination in grading by gender in Israel.

However, our methods are most analogous to the types of field experiments that have been used to measure racial discrimination in labor market settings. These experiments typically measure discrimination in the hiring of actual applicants. The researchers either have actual individuals apply for jobs (Fix and Struyk, 1994) or they may submit fictitious job applications to actual job openings (Bertrand and Mullainathan, 2004; Banerjee, Bertrand, Mullainathan, and Datta, 2009; Siddique, 2008); in both cases, 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-less environment, a major advantage of these experiments is that they are able to measure the behavior of actual employers making real employment decisions.

In our study, we break the correlation between observed characteristics and student quality by randomly assigning characteristics to an exam cover sheet before it is graded. We then place teachers in an environment in which their behavior affects the wellbeing of the child, In particular, teachers know that the results of their grading will result in a substantial prize to the winning child (58 USD or 55.5 percent of the parents' monthly income). Thus, we are able to mimic the incentives faced by teachers in the classroom.

We find evidence of discrimination against lower caste children. Specifically, we find that teachers give exams that are assigned to be "lower caste" scores that are about 0.03 to 0.09 standard deviations lower than those that are assigned to be "high caste." We do not find any overall evidence of discrimination by gender or age. Disaggregating the results by the quality of the exam, the low-performing, low caste children and top-performing females tend to lose out the most due to discrimination. Interestingly, we find that the discrimination against low caste children is driven by low caste teachers, while teachers from the high caste groups do not appear to discriminate at all. Finally, we find that teachers tend to discriminate more towards children who are graded early in the evaluation process, suggesting that teachers use demographic characteristics to help grade when they are not yet confident with a testing instrument.

The rest of the paper proceeds as follows. Section II provides some background on caste discrimination and education in India. Section III describes the methodology, while Section IV describes our data. Our findings are presented in Section V. Section VI provides a discussion of the key results, while Section VII concludes.

II. Background

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

In principle, individuals are now free to choose occupations regardless of caste, but like race in the United States, the historical distinctions have created inequities that still exert powerful social and economic influence.[1] Given the large gap in family income and labor market opportunities between children from lower and high caste groups, it is not that unsurprising that children from traditionally more disadvantaged caste groups tend to have worse educational outcomes than those from the more advantaged groups. For example, Bertrand, Hanna, and Mullainathan (2008) show large differences in 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 socio-economic status, the potential for discrimination in schools is significant. Both urban and rural schools maintain detailed records of their students' caste and religion, along with other demographic information such as their age, gender, and various information on their parents (see, for example, He, Linden, and MacLeod, 2008). Anecdotal evidence suggests that teachers may take this information into account. For example, the Probe Report of India (1999) cites cases of teachers banning lower caste students from joining school. Shastry and Linden (2008) show that caste is correlated with the degree to which teachers are willing to exaggerate the attendance of students enrolled in an educational program that provides grain to high attending students.

III. Methodology

In this section, we first describe the methodology that we designed to understand whether discrimination exists in grading. We then discuss the data and lay out our empirical methodology.

[1] Banerjee and Knight (1985); Lakshmanasamy and Madheswaran (1995); Unni (2002) give evidence of inequality across groups by earnings, while Rao (1992), Chandra (1997), and Munshi and Rosenzweig (2005) show evidence of inequality in social and economic mobility. Deshpande and Newman (2007) and Madeshwaran and Attewell (2007) provide some evidence of discrimination in earnings, while Siddique (2008) and Jodhka and Newman (2007) for discrimination in hiring practices.

A. Research Design

We designed an experiment that comprises of three components: child testing sessions, the creation of grading packets, and teacher grading sessions. We first recruited children to participate in a prized exam competition. After the competition, we copied the tests that the children completed and compiled them into grading packets. Each test copy in the grading packet was assigned an information sheet that included randomly assigned demographic characteristics. We then recruited local teachers to participate in a grading session, during which the teachers graded the exams that displayed the randomly assigned characteristics.

Child Testing Sessions

In April 2007, we ran exam tournaments for children aged seven to fourteen 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 Rs 2500 prize (about $US 58).[2] The project team informed the families that prizes would be distributed to the highest scoring child in each of the two age groups (7 to 10 years of age, and 11 to 14 years of age), that the exams would be graded by local teachers after the testing sessions, and that the prize would be distributed after the grading was complete. The prize is a significant sum of money, given that the parents reported earning an average of 4,500 Rs per month ($US 104) in the parent survey that we administered.

Over a two week period, sixty-eight children attended four testing sessions. The testing sessions were held in various places, such as community halls, empty homes, or temples,

[2] For recruitment, our project team mapped the city: they collected demographic information about each community and also identified community leaders who they might be able to work with later in the project. To ensure that children of varying castes would be present at each session, the team tried to either recruit from neighborhoods where the children were of diverse caste groups or to recruit from several uniform caste neighborhoods.

centrally located to the communities from which the children were selected. They were held on weekends to ensure that they did not conflict with the school day and that parents would be able to accompany the children to the sessions. During the testing sessions, the survey team first obtained informed consent from the parents for both their participation in the parent survey and their child's participation in the tournament. Next, the survey team administered a short survey to the children's parents to collect information on the child (gender, age) and to also collect basic demographic characteristics of the family (income background, employment status of the father, and caste information).

After the survey, the project team obtained written assent from each participating child and began the actual exam. To vary the subjectivity of the exam questions, we included questions that tested the basic math and language skills contained in the standard Indian curriculum, as well as an art section in which the children were asked to display their creativity. The exam took approximately 1.5 hours. All children who participated in the testing session received a reading workbook at the time of the sessions and were told that they would be contacted with information about the prize when grading was complete.

Randomizing Child Characteristics

The key to our experimental design is to break the correlation between the children's actual performance on an exam and the child characteristics perceived by the teacher when grading the exam. In a typical classroom setting, one can only access data on the actual grades teachers assign to students whose characteristics the teachers know. This makes it impossible to identify what grade the teacher would have assigned had another child, with different socio-economic characteristics, completed the exam in an identical manner. Our experimental design allows us to ensure the independence of the exams' quality and the characteristics observed by the teachers.

Specifically, we randomized the demographic characteristics observed by teachers on each exam. Each teacher was asked to grade a packet containing 25 exams. To form these packets, each test completed by a student was stripped of identifying information, assigned an ID number, and photocopied. Twenty-five copies were then randomly selected to form each packet, without replacement, to ensure that the same teacher did not grade the same photocopied test more than once. Each exam in the packet was then assigned a socio-demographic coversheet, which contained the basic demographic information for the "child." This included a child's first name, last name, gender, caste information, and age.[3] However, these child characteristics were randomly assigned from the characteristics of children sitting for the exams. By teacher, we stratified the assignment of the characteristics to ensure that each teacher observed coversheets with the same proportion of characteristics of each type of child, avoiding the possibility that a teacher was assigned to grade children of a single sex or caste. Since most Indian first names are gender specific, the first name and gender were always randomized together. Similarly, many last names are also caste specific and, therefore, we randomized the last name and the caste together.[4] For each teacher, we sampled the name of the child without replacement so that the teacher would not be grading two different exams from the same child.

Caste, age, and gender were each drawn from an independent distribution. We randomly selected the ages of the students from a uniform distribution between eight and fourteen. We ensured that gender was equally distributed among the males and females. Caste was assigned

[3] We also include caste categories (General, Other Backward Caste, Scheduled Caste, and Scheduled Tribe), which are groupings of the caste categories.

[4] While this strategy has the advantage of consistently conveying the caste information to teachers, it does prevent us from identifying the specific channel through which teachers are getting the information. It may be possible, for example, that the name alone is enough to convey the caste of the child.

according to the following distribution. Twelve and a half percent of the exams were assigned each to the highest caste (Brahmin) and the next caste (Kshatriya). Fifty percent of the exams were assigned to the Vaishya Caste and twenty-five percent were assigned to the Shudra Caste.[5]

Each exam was graded by an average of forty-three teachers. Since the "observed" characteristics of the child were randomly assigned, we would expect that these characteristics would be uncorrelated with the exam grade in a world with no discrimination. Any correlation between the "observed" characteristics and exam scores is, thus, evidence of discrimination.

Teacher Grading Sessions

After creating the packets, we recruited teachers to grade the exams. We obtained a listing of schools in the city from the local government, and we divided the schools 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 went down the list until they obtained the desired number of teachers. 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 headmaster of the school to obtain permission to recruit teachers from the school. Once permission was obtained, the project team explained to the teachers that they would like to invite them to participate in a study to understand grading practices. The teachers were told that they would grade the exams of twenty-five children and that they would be compensated for their work with a Rs 250 (about $US 5.80) payment. The project team also informed the teachers that the child who obtained the highest score based on the grading would receive a prize worth Rs 2500 (about

[5] The purpose of this distribution was originally to ensure variation in both caste and the caste categories to which children could be assigned. These classifications are restricted to the lowest two classes and ensure equal distribution among each category, resulting in 75 percent of the exams being assigned to these castes.

$US 58). This prize was designed to establish incentives for the teachers' grading by ensuring that the grades received on the exam have real effects on the well-being of the children, thereby mimicking the incentives faced by teachers in school.

On average, a grading session lasted about two hours for each teacher. At the sessions, the project team first obtained consent. Next, the project team provided the teachers with a complete set of answers for the math and language sections of the test, and the point system per question for all three sections of the test. The project team went through the answer set question by question with the teachers. Teachers were told that partial credit was allowed, but the project team did not describe how partial credit should be allocated. Thus, the teachers had the discretion to allocate partial credit points as they felt appropriate.

Next, the grading portion of the session began. The teacher received twenty-five 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 demographic information, we asked them to copy the information from the cover sheet onto the grade roster. They were then asked to grade the exam and input the total score and the individual grades for each section of the exam—math, language, and art—onto the testing roster.

When a teacher finished grading his or her packet of exams, the project team administered a short survey to the teacher. The survey consisted of questions designed to gauge the demographic characteristics and teaching philosophy of each teacher.

After all the grading sessions were complete, 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.[6]

B. Data Description

We compiled three sets of data: exam scores, parent surveys, and teacher surveys. 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 using the same grading procedures as the teacher, but on a "blind" basis in which they had 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. The set of exam scores includes the total score and a score on each subject (math, hindi, and art).

Each subject was chosen to provide variation in the objectivity with which the individual sections could be evaluated. Math was chosen to be the most objective section and questions covered counting, greater than/less than, number sequences, addition, subtraction, basic multiplication, basic addition, and simple word problems among a few other basic competencies. Language, which was chosen to be the intermediately objective section, included questions covering basic vocabulary, spelling, synonyms, antonyms, and basic reading comprehension, and so forth. Finally, the art section was designed to be the most subjective. In this section, we asked the children to draw a picture of their family doing their favorite activity and then to explain the activity.

[6] As the tests were equally likely to be assigned the characteristics described any negative (or positive effects) received from being assigned particular characteristics should be equal across individual tests, making the overall average a fair assessment of student performance.

We normalized the exam scores of each section and the overall total scores in the analysis that follows, to facilitate comparisons with other studies in the literature. To do so, we pool all of the grades assigned to each test copy by the teachers, and for each exam, subtract the overall mean and divide by the standard deviation of the scores. Each section and the overall exam score are normalized relative to the distribution of the individual scores for the respective measure.[7]

In addition to the test data, we have data from the two surveys we administered. First, we have data from a survey of the children's parents that was conducted in order to collect information on the socio-demographic background of the children. Most importantly for the experiment, this included information on the family's caste, the age of the child, and the child's gender. Second, we have data from the teacher survey, which included basic demographic information as well as questions regarding the types of students that the teachers normally teach. The demographic information included the teachers' religion, caste, the type of school at which they taught (public or private), their 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 teachers' responses to these questions – all of the teachers taught low income students like those in our sample, either in a local public or private school.

C. Empirical Strategy

The random assignment of tests to teachers and children's characteristics to the coversheets should ensure that there is no systematic correlation between the quality of the graded tests, the

[7] In results not presented in this draft, we have also estimated the results normalizing relative to the distribution of blind test scores. Since this is a linear transformation of the dependent variable, it does not affect the hypothesis tests, nor does it affect the magnitude of the estimated results.

characteristics of the grader, and the characteristics on the coversheet. We check this assumption using the following model:

$$z_{ij} = \beta v_{ij} + \varepsilon_{ij} \tag{1}$$

In this equation, z_{ij} is the original characteristic of the exam that was taken by child i and was graded by teacher j. v_{ij} is a vector that is comprised of the randomly assigned characteristics (gender, age, and caste). We use two different specifications for v_{ij}. For our main specification, we include an indicator variable for whether the test was assigned to one of the lower caste groups, allowing us to contrast the treatment of children in the lower caste groups to that of the high. In the specification shown in Appendix Table 2, we use a series of indicator variables for the specific caste groups (Brahmin, Kshatriya, Vaishya, or Shudra) that were assigned.

Using a model similar to Equation 1, we can, then, estimate the effect of the assigned characteristics on teacher test scores:

$$y_{ij} = \beta v_{ij} + \varepsilon_{ij} \tag{2}$$

where the variable y_{ij} is the test score assigned to test i by the teacher j. While the random assignment eliminates the systematic correlation between the true child characteristics and those observed by the teachers, it is possible that small differences in the types of tests assigned to each category will exist in any finite sample. To ensure that our estimates are robust to these small differences, we estimated two additional specifications. First, we include a difference estimator that controls for child characteristics. The difference estimator takes the following form:

$$y_{ij} = \beta v_{ij} + \delta z_{ij} + \varepsilon_{ij} \tag{3}$$

The vector of randomly assigned characteristics is given by v_{ij} as in equation (1), and z_{ij} is a linear control function that includes the true characteristics of the child taking test i. Second, we include a fixed-effects estimator, which takes the following form:

$$y_{ij} = \beta v_{ij} + \delta z_{ij} + \tau_j w_j + \varepsilon_{ij} \tag{4}$$

where w_j is the grader fixed effects. This specification allows us to control for fixed differences in grading practices across teachers.

IV. DESCRIPTIVE STATISTICS AND INTERNAL VALIDITY

In this section, we first provide descriptive statistics on the characteristics of the children who sat for the exam and the teachers who graded it. Next, we explore whether the original characteristics of the child predicts the exam score. Finally, we provide a check on the randomization.

A. Baseline Data

In Table 1, we provide descriptive statistics on the 120 teachers who participated in the exam competition. Panel A provides information on the demographic characteristics of the teachers, while Panel B provides sample statistics on their caste identity and beliefs. In Column 1, we provide the summary statistics for the full sample. In the subsequent columns, we disaggregate the data by their basic demographic characteristics: 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, and finally, we divide the sample by the teachers' education level in Columns 6 and 7.

Reflecting the fact that teaching (especially at a public school) is a well-paid and desirable occupation, sixty-eight percent of the teachers identify themselves as belonging to the upper caste groups (Panel A, Column 1). Teachers tend to be relatively young (an average age of thirty five) and female (seventy-three percent). We made a point to recruit at both public and private schools. The effort was successful in that we recruited a fairly equal number of teachers across the two groups into the sample. Forty-four percent of the teachers work in public schools, while fifty-six percent work in private schools. About half the sample holds a master's degree.

As Panel B demonstrates, caste identity is high among the teachers. Sixty-four percent report that their closest friend is of the same caste grouping and forty-one percent report that they belong to a caste association. Interestingly, even the teachers themselves tend to report that they believe that "teachers favor some students over others in their grading for reasons unrelated to educational performance." Eighty-one percent of the teachers agreed with this statement.

Comparing the characteristics of teachers across Columns 2 through 7, the relationships between the various characteristics generally follows the expected patterns. Low caste teachers are more represented in the comparatively less desirable private school teaching positions, less likely to have a master's degree, more likely to be male, and more likely to belong to a caste association (Columns 2 – 3). Female teachers tend to belong to the high caste groups (75 percent for versus 48 percent for men) and are also more likely to have a master's degree (Columns 4 – 5). The somewhat surprising pattern lies in the relationship between education and beliefs (Panel B, Columns 6 – 7). We do not observe a difference in caste identity or beliefs across those with and without a master's degree.

In Table 2, we provide summary statistics for the children who participated in the exam competition and the characteristics observed by the teachers. We describe the original characteristics of the children and the characteristics of the children observed by the teacher in Columns 1 and 2, respectively. Column 1 contains averages for the actual sixty-nine children, while Column 2 contains averages for the 3,000 exam copies graded by the teachers. Standard deviations are provided in parentheses below each average.

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. In our sample, eighteen percent of the children originally belonged to the high caste group, while only twelve percent were assigned to the lowest caste group. Despite an effort to recruit children from the lowest caste, only six percent originally come from the Shudra group. As we were interested in the effects on this specific subgroup, we increased the observed in this category to twenty-five percent. In Panel C, we show the average age and gender of the children. The mean observed age of the children (11 years) is approximately the same as the mean age of children in the sample (10.9 years). To maximize power, we elected to have equal sized gender groups, and therefore, there are more females in the observed sample (50 percent) as compared to the actual sample (43 percent).

Table 3 provides a description of the average quality of the tests taken by the children. Rather than the normalized scores used in the rest of our analysis, we provide the test score measures as the fraction of total possible points, for easy interpretation. On average, students scored a total of 63 percent on the exam. Students scored the lowest in art (47 percent) and the highest in math (68 percent).

The data suggest that the grading of the exam's art section may have been more subjective than the grading of the math or language sections. 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). In addition, the variance on the math and language sections of the exams are almost equal at 0.23 and 0.16 percentage points, respectively, on both the teacher and the blind test scores. On the other hand, the average art scores given by the teacher are much lower, with a mean of 47 percent for the teachers compared with 64 percent for the blind graders. Moreover, the larger variance for the art section (0.32) provides confirming evidence that, as intended, the art section may have been more subjective than the other sections of the exam.

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. The score ranges per exam are quite large, particularly at the lower portion of the test quality distribution. This indicates that the teachers assign partial credit very differently.

Who won the exam competition? In reality, low caste females won both age categories. The two winning exams each displayed the low caste characteristics about 80 percent of the time. About half the time, the winning exams were assigned as female and the average age on the winning exams was eleven years old. Thus, the winning exam was, on average, assigned the mean characteristics in our sample, as we would predict given the randomization.

B. Do Actual Characteristics Predict Exam Scores?

We next investigate the relationship between the actual characteristics of the children in our sample and their exam scores. In the first column of Table 4, we present the simple correlation between the total test scores that the teachers assigned to the exams and the true underlying characteristics of the children. In Column 2, we add the blind test score as an additional control. In Columns 3 -5, we disaggregate the test scores by individual subjects. All scores have been normalized relative to the overall distribution of scores for each respective section.

The children's original demographic characteristics strongly predict the exam scores. Children from the lower caste group score about 0.41 standard deviations worse on the exam than the high caste group (Column 1).[8] Females, on average, score 0.18 standard deviations higher on the exam than males. Finally, one additional year of age is associated with an additional 0.85 standard deviations in score, although this effect is declining with years of age.

In Column 2, we replicate the specification in Column 1, adding the score that our blind grader awarded to each exam as an additional control variable. The blind score provides us with a measure of performance on the exam that reflects only the underlying quality of the exam. Any difference between the test scores from the teachers and the scores from the blind grading can be attributed partially to discrimination, but also to the natural variation in grading practices. The total blind score awarded to the test is highly correlated with the score that the teachers assigned to the tests. On average, a one standard deviation increase in the blind scores results in a 0.93 standard deviations increase in the total test score. When we include the blind test score, the coefficients on the low caste and female indicator variables more closer to zero, but the age variable still is a significant predictor of the final score.

We, next, disaggregate the test score data by subject in Columns 3 – 5 of Table 4. The results suggest that the different sections of the exam do provide variation in subjectivity, with the art section being much more subjective than the other sections. The correlation between the blind score and the teacher's score for the math and language sections is the same as for the overall score (about 0.93). The art section, however, has a coefficient that is only 0.63. Even when including the blind test score, the original caste status significantly predicts the math and art scores and the child's original age still predicts the test scores in all three subjects.

[8]Appendix Table 1 replicates the table including disaggregated caste groups. Recall that the caste groups in terms of descending order of prestige are the Brahmin, Kshatriya, Vaishya, and Shudra castes. Children who belong to Kshatriya caste perform worse (-0.17 standard deviations) than the students who belong to Brahman caste, which is the omitted category in the regressions (Column 1). Children from the Vaishya caste then score worse than the students from the Kshatriya caste by 0.35 standard deviations, and children who belong to the Shudra group score the worst (-1.17 standard deviations lower than the children from the Brahman caste).

C. Internal Validity

In order to determine whether discrimination exists, we must first confirm that the average characteristics assigned to each test during the randomization process are effectively the same. We can test for this in two ways. First, we can verify this by regressing the actual characteristics of the children on each exam on the characteristics assigned to the exams by the random assignment process (Table 5, Column 1 – 3). Second, we can regress the test scores from the blind grading of the exam on the characteristics assigned to the exams (Columns 4 – 7). For each specification, we present the coefficients on each observed characteristic, as well as the F-statistic from the joint hypothesis test of the statistical significance of all the observed characteristics. For convenience, we also provide the p-value of the joint test.

The results described in Table 5 demonstrate that the random assignment process succeeded in assigning characteristics to the cover sheets that are, on average, uncorrelated with the actual characteristics or performance of the children. With the exception of the fact that tests from actual females are more likely to be assigned to a lower age group, none of the other coefficients are significant. In terms of magnitude, all of the coefficients are practically small; almost every coefficient is less than 1/10 of a standard deviation. The chi-square estimates provide further evidence that the assigned characteristics are uncorrelated with the actual exams. Of the seven estimated equations, none are statistically significant at the 10 percent level. In particular, as shown in Column 4, we find little correlation between all of the assigned characteristics and the quality of the exam, as measured by the blind test score (p-value of .64).[9]

[9] In Appendix Table 2, we disaggregate the exam data by individual caste group. The table further confirms that the randomization was successful, as the individual castes are uncorrelated with the actual characteristics and the blind test score.

V. Results

We now turn to our experimental results. In Section A, we test for the overall levels of discrimination and we also measure the discrimination effects by place within the test score distribution. In Section B, we study whether the parameters we set for the test—grading order and test type— affect how teachers grade. Finally, in Section C, we compare the relative degree of discrimination both across the children's specific caste groups and across teachers who possess different demographic characteristics.

A. Overall Results

In Table 6, we present the results of the regression of the exam scores on observed caste. In Column 1, we provide the overall effects of the observed caste on the test scores assigned by the teachers. Given the randomization, we do not necessarily need to include control variables for the characteristics of the child and the teacher. However, doing so may provide us with greater precision. Therefore, in Column 2, we present the results of specifications in which we control for the actual child's baseline characteristics. In Column 3, we present the results of the specification that includes the grader fixed effect. As a robustness check, we additionally control for the blind test score in Column 4. The blind test score can be viewed as another measure of the underlying characteristics of the child who took the exam.

We first examine the results on caste. Looking at Column 1, we find that the teachers gave, on average, the exams assigned as "low caste" test scores that were 0.09 standard deviations lower than an exam that was assigned to be from the "high caste" group (significant at the ten percent level).[10] Controlling for child characteristics (Columns 2) and teacher fixed

[10] 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 the

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 -0.027 (Column 3). The estimate, however, remains statistically significant at the ten percent level.

Our results suggest that while discrimination may be present, the magnitude of the overall effect is relatively small when compared to the actual differences in test scores across the caste groups. The caste gap due to discrimination from our preferred specification in Column 3 (including teacher fixed effects and original characteristics control variables) is -0.086, which is much smaller than the actual 0.41 standard deviation gap described in Table 3.[11] The effect size falls within the lower tail of the distribution of the impacts of various education interventions in the developing world that have been evaluated by randomized experiments. Successful interventions have typically fallen within a 0.07 to 0.24 standard deviation range; this range includes evaluations of programs that provide additional teachers (Banerjee, Cole, Duflo, and Linden, 2007), teacher monitoring and incentive programs (Duflo, Hanna, and Ryan, 2007; Glewwe, Illias, and Kremer, 2003), tracking programs (Duflo, Dupas, and Kremer, 2008), scholarships for girls (Kremer, Miguel, and Thornton, 2007), and contract teachers (Muralidharan and Sundararaman, 2008).

Interestingly, we do not find any effect of assigned gender or age on total test scores, regardless of specification (Table 6). Note that in addition to not being significant, the

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indicator variable for the lower castes measures the difference between the lower castes and the highest caste. We cannot assess, for example, whether teachers are biased in favor of high caste children or against lower caste children.

[11]The finding that discrimination accounts for only a small percentage of the difference between groups has been documented in other settings, such as Levitt (2004), who finds that, when discrimination is present, it is not the leading factor of how people vote in the game show the weakest link.

magnitudes of the effects are very small. For example, being labeled with an additional year of age provides between a 0.001 – 0.003 increase in score.

In Table 7, we test whether the underlying exam quality influences the teacher's actions. In Column 1, we interact the blind test score with the observed characteristics and control for the blind test score, using the following equation:

$$y_{ij} = \beta v_{ij} + \lambda q_i + \eta v_{ij} * q_i + \delta z_{ij} + \tau_j w_j + \varepsilon_{ij} \tag{5}$$

where q_i is the blind test score for test i. We find that the teachers grade the low caste exams down by 0.029 standard deviations. However, possessing a higher quality exam mitigates this effect. Specifically, a one standard deviation increase in the blind test score leads to a 0.03 standard deviation increase in the difference between the low caste and high caste groups (statistically significant at the ten percent level).

We next create a variable that indicates whether an exam possesses a high underlying quality. Specifically, the variable equals 1 if the blind test score is above average and equals zero otherwise. We then estimate a specification that includes the interactions of this variable with each of the assigned demographic characteristics. We find that teachers grade the below average exams that were assigned to be low caste down by -0.108 standard deviations (statistically significant at the 5 percent level). However, they grade the exams that are high quality up by 0.083; however, it is important to note that this effect is only statistically significant at the 20 percent level. Thus, there is some evidence that teachers help low caste children who show some promise, but hurt low caste children that match perceived stereotypes. Interestingly, we also see that teachers grade low quality exams that were assigned to be female up by 0.107 standard deviations (significant at the 1 percent level), but then grade the high quality exams down by the almost the same magnitude (significant at the 1 percent level). Thus, while on average girls do not appear to be discriminated against, top performing girls tend to be assigned lower grades than high performing boys for similar quality work.

To provide additional detail on the relationship between caste discrimination and test quality, we construct a non-parametric estimate of the relationship between the score assigned to the exam and the score from the blind grading. The estimates are constructed using a local linear polynomial estimator (bandwidth of 0.4) and are presented in Figure 2. The solid line represents the scores assigned to tests labeled as high caste and the dashed line represents the scores assigned to the tests labeled as lower caste. There is a clear break that emerges in the data at about -1.1 standard deviations, in which the high caste children are consistently scored higher than the lower caste children. To estimate this directly, we interact the lower caste indicator with an indicator for having a blindly graded score below -1.1 standard deviations (Column 3 of Table 7). Consistent with Figure 2, lower caste children with a blind test score below -1.1 standard deviations score, on average, -0.15 standard deviations lower than their high caste peers.

B. Parameters of the Exam

In addition to discriminating for (or against) particular types of children, it is also possible that teachers may be more likely to discriminate in particular types of situations. To explore these types of issues, we incorporated two features into the exam: the random ordering of grading and exam sections with varying levels of subjectivity.

For each teacher, we created a packet in which we specified the order in which teachers should grade the exam. Therefore, for each teacher, we know which exams were graded first and which exams were graded towards the end. Using this knowledge, we can test whether teachers discriminate more at the start of the packet, when they were first getting used to the format of the particular test. In Column 1 of Table 8, we show the results between the interaction of the observed characteristics and the place in the grading order (which varies by teacher from 1 to 25), controlling for the place in the grading order in which the exam was graded. In Column 2, we show the results of the interaction between the observed characteristics and a variable that indicates that the exam was graded in the first half of the teacher's pile. All regressions include the original test characteristics and the grader fixed effect.

We find that the grading order matters. Teachers mark exams that are assigned to be low caste 0.23 standard deviations lower (significant at the 5 percent level; Column 1). However, as grading order increases, the difference is mitigated. As shown in Column 2, being graded in the first half of the packet implies a 0.12 standard deviation gap between the exams that were assigned to be low and high caste (although this is only significant at about the 20 percent level) and a 0.10 gap between the exams that were assigned to be female and male (significant at the 1 percent level). Figure 3 illustrates this low versus high caste comparison graphically. The x-axis is the order in which the exams were graded. The dotted line signifies the assigned scores for the low caste group, while the straight line signifies this for the high caste group. As in the regression analysis, we find a gap in test scores between the low and high caste groups at the start of the grading order, but this effect fades as the place in the grading order increases.

Taken together, these results start to suggest that when teachers are not confident with a testing instrument, discrimination is most likely to occur. It appears that when grading students early in the process, when the overall distribution of scores is unknown, teachers may use the caste of a student not as a signal of performance, but rather as a signal of where the child will eventually land in the overall distribution of tests. This also suggests that programs that improve teacher skills and comfort level with testing instruments, may also potentially reduce the discrimination seen in the classroom. While this is not something we can fully verify in the context of this particular experiment, it provides guidance for future work.

The second feature we attempted to incorporate into the exam was the level of subjectivity of the exam questions. It is possible, for example, that the effects may be small if the teachers have little leeway in assigning points to the exam questions. We specifically included sections on the exam that had different levels of subjectivity. And as demonstrated in Table 2, the relative subjectivity of these sections is borne out by the significantly lower correlations between blind and non-blind scores on the exam's art section relative to the other sections. In Table 9, we present the results disaggregated by subject. All specifications include the original test characteristics and grader fixed effects as controls. Interestingly, we do not see significant differences across the three subjects. Even on the art section, the observed reduction in test scores for lower caste students is similar to the estimates for 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 per question. 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, in the end, all exams provided the teachers with some level of discretion.

C. Specific Characteristics of the Child and Teacher

We, next, explore whether the results differ by the specific caste group of the child and whether different types of teachers exhibit different degrees of discrimination.

In Table 10, we show the results by disaggregated caste groups. While observed gender and age are still included in the specification, the results are near identical to Table 6 and, therefore, we omit them from the tables for conciseness. All specifications also include the original test characteristics and grader fixed effects. In Column 1, we show the main effects of each caste. In Columns 2 and 3, we provide the results of specifications that include the interaction of the caste variable with the blind test score and an indicator variable for an above average score on the blind test, respectively. Recall that the caste groups in terms of descending order of prestige are the Kshatriya, Vaishya, and Shudra.

We find significant differences between the exams that were assigned as belonging to the high caste groups and exams that were assigned as belonging to either the Kshatiya and Shudra groups (Column 1); the effect on exams that were assigned as belonging to the Vaishya group, while negative, is not significant at conventional levels (significant at 15% level). We cannot reject the hypothesis that the coefficients on the three observed caste variables are significantly different from one another. The results from Column 2 and Column 3 are consistent with those from Table 7. Having an above average test scores increases the average scores for individuals labeled as the lower caste groups, relative to those labeled as high caste. This effect is particularly strong for the highest of the low caste groups (Kshatriya).

Finally, we explore whether teachers differ in the degree to which they use students' observed characteristics as proxies for actual performance. We focus on the four key characteristics that are the most theoretically relevant. First, we explore whether the caste and gender of the teacher affects the observed levels of discrimination. For example, teachers' beliefs on the average characteristics of children from a particular caste may be influenced by their own caste. Lower caste teachers, for example, may be less likely to use caste as a proxy for performance given their intimate experience with low caste status or may feel partial towards helping someone from their own social group (in-group bias). On the other hand, such teachers may have internalized a belief in the difference in ability as a means of rationalizing historical experience. Thus, low caste teachers may discriminate more against very low status children.[12] We test for the presence of in-group bias among the teachers in our sample in regards to caste and gender. In addition, we estimate whether the degree of discrimination varies by the teachers' education levels or age. More educated teachers may be more aware of and more tolerable of diversity, whereas older teachers may have more experience with individuals of different backgrounds or more experience with children of various backgrounds through more teaching experience.

We present the results of our analysis in Table 11. 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 difference between the coefficients. In Column 4, we present results of a specification that includes the interactions between the observed caste variables and all four teacher demographic variables. All regressions include both original test characteristics and grader fixed effects.

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 as belonging to the lower caste and

[12] Previous studies exploring how belonging to a group impacts a person's treatment of others in that group have found, for the most part, evidence of in-group bias (positive discrimination towards members of your own group). A series of experiments in the psychology literature have found that individuals presented in-group bias in 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. Using data from the game show "The Weakest Link," Levitt (2004) find that some evidence that men vote more for men and women vote more for women. For a good description of theory and literature of in-group bias the work of Anderson, Fryer, and Holt (2006).

those assigned as belonging to the high caste for teachers of the high caste (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 0.2 standard deviations—and significant at the 10 percent level (Column 3). Of course, as described in Table 1, lower caste teachers tend to come from a different socio-economic background than upper caste teachers (more likely to be male, less likely to have a master's degree, etc), and these characteristics may account for the results we find, rather than caste. To control for these possible confounds, in Column 4, we control for both the main characteristics and the interactions of the characteristics with the observed low caste status. The results remain the same: lower caste teachers significantly downgrade exams that are assigned to be lower caste, relative to the high caste teachers.

Turning to gender, we also do not observe in-group bias. We do not see a significant difference in the way female and male teachers grade exams that are randomly assigned to be male versus female. In terms of caste, we observe that female teachers significantly grade down 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. Moreover, while the coefficients are similar, the sample size of the male teachers is much smaller (33 male teachers versus 87 female teachers), which may account for the higher variance in the estimates for the male teachers.

While we find no significant difference in caste discrimination by teachers' education or age, we find that more educated teachers and older teachers are more likely to give higher grades to exams that were assigned to be female.

VI. DISCUSSION

We find that teachers provide exams that are assigned to be "lower caste" scores that are about 0.03 to 0.09 standard deviations lower than those that are assigned to be "high caste." What is the underlying model that drives these results? Economic theories of discrimination fall into two main categories. The first type of models falls under the category of taste-based discrimination, in which teachers may have particular preferences for individuals of a particular group or characteristic. The second class of theories encompasses statistical discrimination, in which teachers may use observable characteristics to proxy for unobservable skills.

The empirical design should eliminate the possibility of statistical discrimination, as teachers observe a measure of skill for the child: the actual performance on the exam. However, one can imagine a series of situations where the teacher may statistically discriminate. First, the teacher may be lazy, and may not be invested in carefully studying the exam to determine the skill level for each child. Thus, they may use the demographic variables to instead proxy for skill. While we cannot fully rule out this story, the fact that the teachers knew that a fairly large prize was at stake increased the seriousness of the exercise When they were confused, the teachers asked the project team questions on the grading and all of the teachers seemed to spend a fair bit of time grading each exam. Moreover, if teachers were lazy, we may 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 observe the opposite: teachers gave a considerable amount of partial credit for wrong answers. Thus, it does not appear as though the teachers were slacking.

Second, teachers may statistically discriminate if they are not confident about the testing instrument. In particular, teacher may be unsure about what is the right level of partial credit to give per question and they may be also unsure about what the final distribution of grades will look like. Thus, 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. The data lends some credence to this theory: discrimination tends to occur at the start of the grading order and fades over time.

On the other hand, there is also considerable evidence that the discrimination is taste-based. First, if we expected the teachers to be statistically discriminating, we would expect them to use observed age to make predictions on the skills of the child, as the age variable has much more predictive power on test scores than caste. However, they tend to discriminate on caste, but not age. Thus, these results can imply taste-based discrimination, rather than just statistical discrimination. Note, however, that we cannot rule out the fact that teachers have incomplete information, or are just bad at making statistical predictions of how children of particular groups will fare on the exams.

Second, the gap in scores based on demographics varies by the quality of the exam: low caste children are hurt when their exam quality is low to begin with and females are hurt when their exams are of high quality. If the teachers were conducting statistical discrimination, we may not expect quality to matter as much.

VII. 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 teachers systematically discriminate against them. Through an experimental design, we find evidence that teachers discriminate against low caste children in grading exams. For example, we find teachers give exams that are assigned to be upper caste test scores that are, on average, 0.03 to 0.09 standard deviations higher than those assigned a lower caste classification. We do not find any overall evidence of discrimination by gender or age. Disaggregating the results by the quality of the exam, the low-performing low caste children and top-performing females tend to lose out the most due to discrimination. Quite interestingly, we find that the discrimination against low caste students is driven by low caste teachers, while those teachers from the higher caste do not appear to discriminate at all.

It is important to note that our study only reflects upon one element of discrimination within the classroom. Discrimination may also exist in other forms: calling on students of particular groups but not others, discouraging those of certain groups from furthering their education, and so forth. If, as we show, discrimination exists in the subtle grading of an exam, other more blatant types of discrimination may exist as well. Therefore, our results provide additional motivation for research to investigate how the treatment of children within the classroom differs by race, ethnicity, and gender.

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Table 1: Characteristics of the Teachers

Characteristic	All (1)	Caste: High Caste (2)	Caste: Low Caste (3)	Gender: Female (4)	Gender: Male (5)	Education: No Master's (6)	Education: Master's (7)
Number of teachers	120	81	39	87	33	61	59
A. Teacher Characteristics							
Upper 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
B. Teacher Beliefs							
Closest Friend: Same Caste Grouping	0.64	0.74	0.44	0.72	0.42	0.66	0.63
Belong to a Caste Association	0.41	0.39	0.46	0.44	0.33	0.42	0.41
Believe that teachers favor some students over others in their grading for reasons unrelated to their educational performance	0.81	0.83	0.77	0.82	0.79	0.80	0.81

Notes:

1. This table summarizes the characteristics and beliefs of the 120 teachers who participated in the grading sessions.

Table 2: Child Characteristics

	Original (1)	Observed (2)
A. High Caste		
Brahmin	0.18	0.12
	(0.39)	(0.33)
B. Lower 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)	
C. Other		
Female	0.44	0.50
	(0.50)	(0.50)
Age	10.95	10.98
	(2.04)	(2.00)

Notes:

1. This table summarizes both the real characteristics of the children in our sample and the characteristics observed by the teachers.
2. The original (true) characteristics, listed in Column 1, include data on all 69 children who completed a test and a demographic survey.
3. Column 2 provides data on the characteristics that were randomly assigned to the cover sheets of the tests that the teachers graded. This column summarizes the data from the 3,000 coversheets in the study (25 for each of 120 teachers).

Table 3: Description of Test Scores

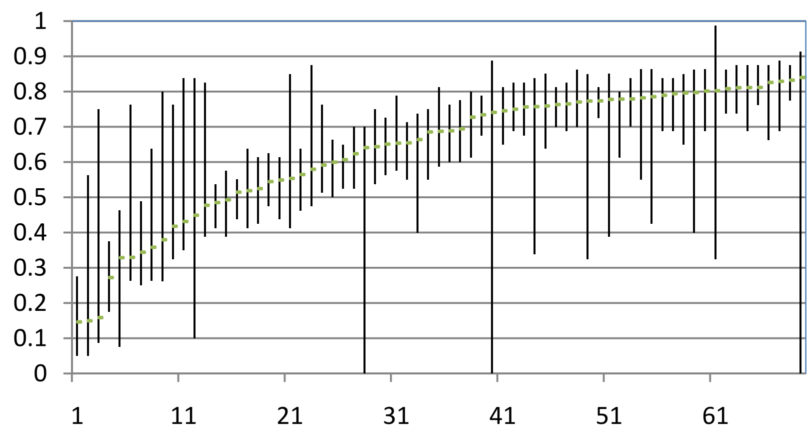
	Teacher Scores	Blind Test Score
	(1)	(2)
A. Test Score		
Total	0.63	0.67
	(0.19)	(0.19)
B. Test Scores, By Exam		
Math	0.68	0.70
	(0.22)	(0.23)
Hindi	0.55	0.58
	(0.16)	(0.16)
Art	0.47	0.64
	(0.32)	(0.35)
Observations	3000	69

Notes:

1. This table summarizes the test scores from the exam tournament. The scores are presented in terms of the percentage of total possible points.

2. 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:

1. Figure 1 provides the range of test scores (in percentages) given by the teachers for each of the 69 exams used in the study.

Table 4: Correlations between Original Characteristics and Final Test Scores

Test Type:	Total	Total	Math	Hindi	Art
	(1)	(2)	(3)	(4)	(5)
Constant	-5.348	-0.927	-0.941	-0.97	-1.094
	(0.416)***	(0.164)***	(0.169)***	(0.191)***	(0.330)***
Low Caste	-0.409	-0.013	-0.026	0.008	-0.111
	(0.037)***	(0.014)	(0.015)*	(0.017)	(0.029)***
Female	0.183	-0.011	0.006	-0.001	0.004
	(0.029)***	(0.011)	(0.012)	(0.013)	(0.023)
Age	0.846	0.142	0.164	0.133	0.147
	(0.079)***	(0.031)***	(0.032)***	(0.036)***	(0.062)**
Age^2	-0.03	-0.006	-0.007	-0.005	-0.007
	(0.004)***	(0.001)***	(0.001)***	(0.002)***	(0.003)**
Blind Test Score		0.926	0.929	0.932	0.634
		(0.007)***	(0.007)***	(0.008)***	(0.014)***
Observations	3000	3000	3000	3000	3000
R-squared	0.28	0.89	0.9	0.85	0.5

Note:

1. This table contains the raw correlations between the grades awarded to the exams by teachers and the children's original, unobserved characteristics.

2. The first two columns contain results for the total test score, with and without controlling for the blind test scores. Columns 3 - 5 present the results, controlling for the blind test score, by exam section.

3. Child performance on each exam is measured using the score normalized to the overall exam score distribution.

4. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Table 5: Randomization Check

	Actual Characteristics			Blind Scores			
	Low Caste	Female	Age	Total	Math	Hindi	Art
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low Caste	-0.035	0.006	-0.071	-0.068	-0.062	-0.064	-0.054
	(0.021)	(0.027)	(0.113)	(0.054)	(0.055)	(0.054)	(0.055)
Female	-0.02	-0.022	-0.022	0.012	0.031	-0.001	-0.02
	(0.014)	(0.018)	(0.075)	(0.036)	(0.036)	(0.036)	(0.036)
Age	-0.063	-0.100	0.053	-0.014	0.045	-0.076	-0.007
	(0.045)	(0.058)*	(0.237)	(0.114)	(0.115)	(0.114)	(0.115)
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	3000	3000	3000	3000	3000	3000	3000
F-Stat	1.85	1.17	0.25	0.43	0.64	0.48	0.89
P-Value	0.1157	0.3215	0.9082	0.7889	0.6358	0.7501	0.4682

Note:

1. 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 a teacher.

2. The F-statistic and p-value provide a test of joint significance of the observed characteristics.

3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Table 6: Effect of Observed Characteristics on Total Test Scores

Observed Characteristics	(1)	(2)	(3)	(4)
Low Caste	-0.09	-0.087	-0.086	-0.027
	(0.054)*	(0.044)**	(0.043)**	(0.017)*
Female	0.022	0.015	0.014	0.008
	(0.036)	(0.029)	(0.029)	(0.011)
Age	0.001	0.003	0.003	0.001
	(0.009)	(0.007)	(0.007)	(0.003)
Original Test Characteristics		YES	YES	YES
Grader Fixed Effect			YES	YES
Blind Test Score				YES

Note:

1. Table 5 presents the regression of total normalized test scores on observed characteristics that were randomly assigned to the coversheets of test copies.

2. The sample includes the 3,000 graded exams (graded in sets of 25 by 120 teachers).

3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Table 7: Effect on Test Scores, by Exam Quality

Observed Characteristics	(1)	(2)	(3)
Constant	-1.175	-3.264	5.04
	(0.185)***	(0.328)***	(0.834)***
Low Caste	-0.029	-0.108	-0.066
	(0.017)*	(0.049)**	(0.058)
Female	0.008	0.107	-0.008
	(0.011)	(0.032)***	(0.035)
Age	0.001	0.000	-0.008
	(0.003)	(0.008)	(0.009)
Low Caste * Blind Test Score	0.03		
	(0.018)*		
Female * Blind Test Score	-0.015		
	(0.011)		
Age * Blind Test Score	-0.002		
	(0.003)		
Blind Test Score	0.921		
	(0.036)***		
Low Caste * Above Average Blind Score		0.083	
		(0.062)	
Female * Above Average Blind Score		-0.11	
		(0.040)***	
Age* Above Average Blind Score		-0.004	
		(0.010)	
Above Average		1.508	
		(0.128)***	
Low Caste * Blind Score < -1.1			-0.153
			(0.091)*
Female * Blind Score < -1.1			0.054
			(0.056)
Age * Blind Score < -1.1			0.002
			(0.014)
Blind Score < -1.1			-1.726
			(0.175)***
Original Test Characteristics	YES	YES	YES
Grader Fixed Effect	YES	YES	YES

Notes:

1. This table explores whether discrimination varies by exam quality.

2. The outcome variable is the total normalized test score.

3. In Column 1, we interact the observed characteristics with the blind test score, while we interact the observed characteristics with an indicator for above average blind score in Column 2. In Column 3, we interact the observed characteristics with an indicator for below 1.1 standard deviations.

4. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).

5. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Figure 2: The Caste Gap, by Blind Test Score

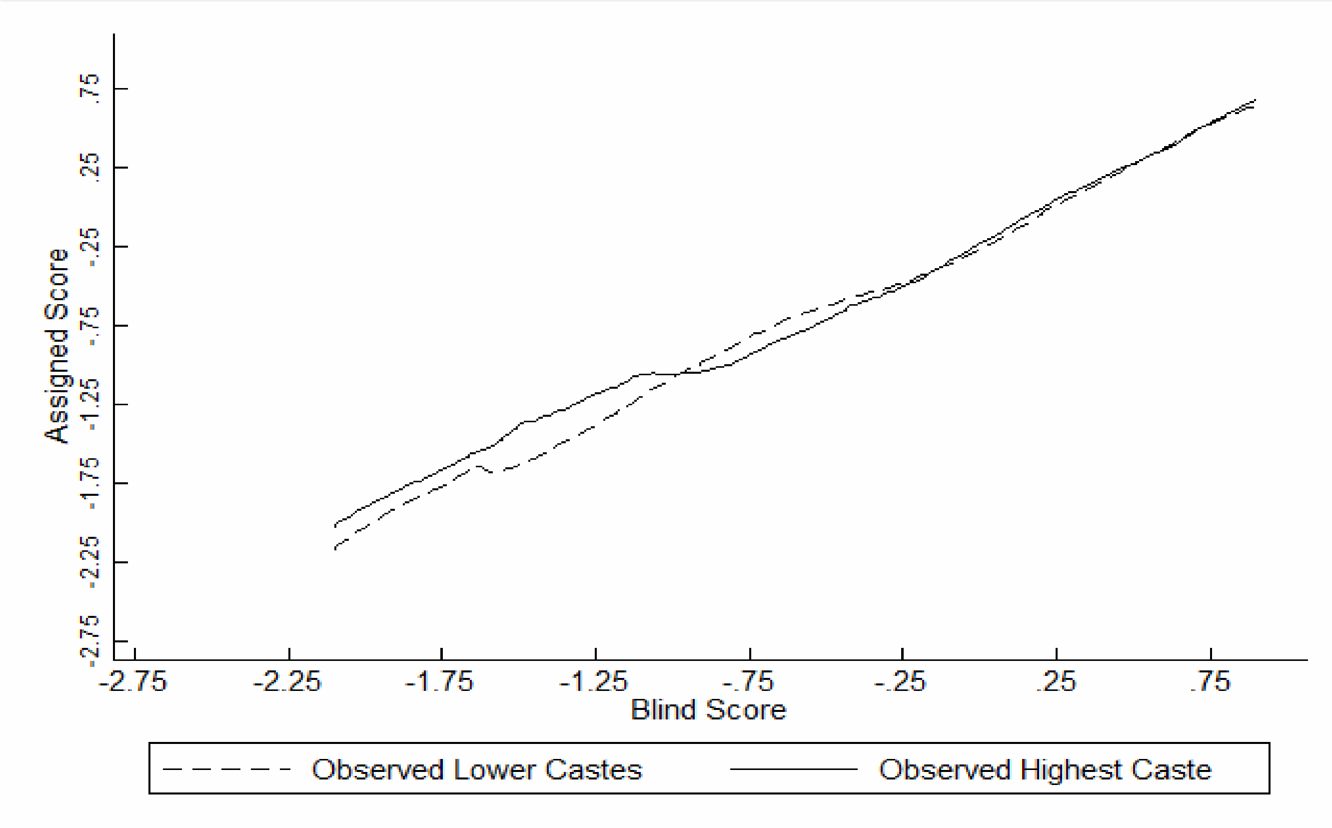


Table 8: Effect on Test Scores, by Grading Order

Observed Characteristics	(1)	(2)
Constant	-5.657	-5.872
	(0.500)***	(0.479)***
Low Caste	-0.233	-0.03
	(0.093)**	(0.058)
Female	-0.098	0.063
	(0.060)	(0.040)
Age	0.004	-0.002
	(0.015)	(0.010)
Low Caste * Grading Order	0.011	
	(0.006)*	
Female * Grading Order	0.009	
	(0.004)**	
Age * Grading Order	0.000	
	(0.001)	
Grading Order	-0.014	
	(0.013)	
Low Caste * Start of Grading Order		-0.120
		(0.089)
Female * Start of Grading Order		-0.102
		(0.058)*
Age* Start of Grading Order		0.01
		(0.015)
Start of Grading Order		0.035
		(0.184)
Original Test Characteristics	YES	YES
Grader Fixed Effect	YES	YES

Note:

1. This table explores whether the order in which the exam was graded affects the treatment of exams assigned by observable characteristics.

2. Grading order is a variable that gives the order of the exam as graded by the teacher. This variable ranges from 1 (1^{st} exam graded) to 25 (last exam graded). Start of grading order is an indicator variable that equals one if grading order is less than or equal to twelve, and zero otherwise.

3. The outcome variable is the total normalized total score.

4. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).

5. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Figure 3: The Caste Gap, by Grading Order

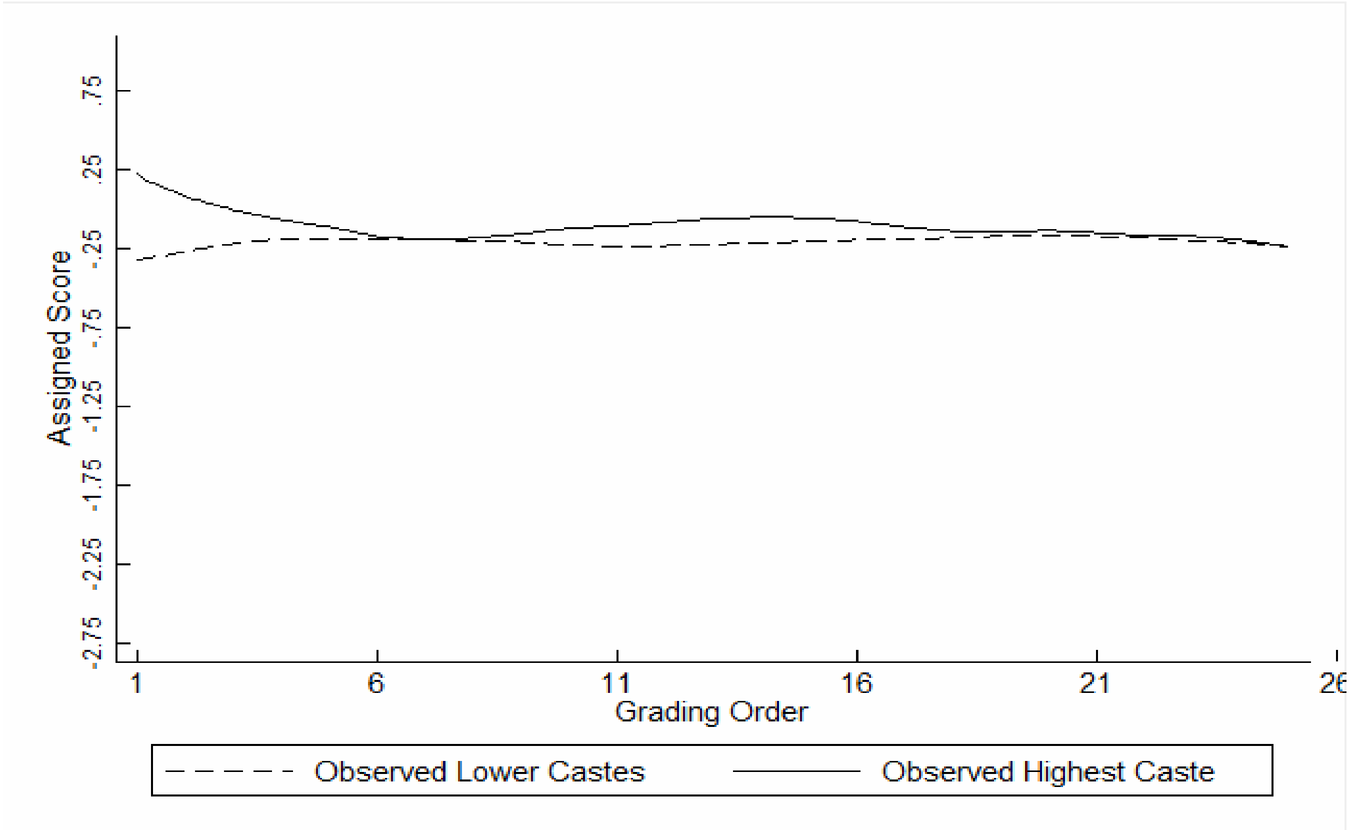


Table 9: Effect on Test Scores, by Subject

	Math	Hindi	Art
	(1)	(2)	(3)
Low Caste	-0.072	-0.08	-0.058
	(0.043)*	(0.047)*	(0.042)
Female	0.024	-0.004	0.011
	(0.029)	(0.031)	(0.028)
Age	0.007	0.001	-0.005
	(0.007)	(0.008)	(0.007)
Original Test Characteristics	YES	YES	YES
Grader Fixed Effect	YES	YES	YES

Note:

1.This table presents the regression of normalized test scores for the indicated sections of the exam on the observed characteristics that were randomly assigned to the coversheets.

2. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).

3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Table 10: Effect of Detailed Caste Groups on Total Test Scores

Observed Characteristics	(1)	(2)	(3)
Constant	-5.892	-1.18	-3.275
	(0.471)***	(0.185)***	(0.328)***
Kshatriya	-0.112	-0.03	-0.206
	(0.057)*	(0.022)	(0.065)***
Vaishya	-0.067	-0.023	-0.083
	(0.045)	(0.017)	(0.051)
Shudra	-0.112	-0.042	-0.114
	(0.050)**	(0.019)**	(0.056)**
Kshatriya * Blind Test Score		0.028	
		(0.023)	
Vaishya * Blind Test Score		0.029	
		(0.018)	
Shudra * Blind Test Score		0.033	
		(0.020)	
Blind Test Score		0.92	
		(0.037)***	
Kshatriya * Above Average Blind			0.187
			(0.082)**
Vaishya * Above Average Blind			0.06
			(0.065)
Shudra* Above Average Blind			0.081
			(0.071)
Above Average			1.495
			(0.128)***
Original Test Characteristics	YES	YES	YES
Grader Fixed Effect	YES	YES	YES

Note:

1. This table presents estimates of the effect of observed caste disaggregated by specific

2. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).

3. The outcome variable in all regressions is the normalized total score.

4. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Table 11: Effect on Test Scores, by Teacher Type

Teachers of the indicated category?	Yes	No	Difference	Difference (Conditional on other teacher characteristics)
	(1)	(2)	(3)	(4)
		A. Upper Caste		
Low Caste	-0.023	-0.227	0.197	0.204
	(0.052)	(0.078)***	(0.093)**	(0.098)**
Female	-0.01	0.059	-0.071	-0.058
	(0.035)	(0.051)	(0.061)	(0.065)
Age	0	0.008	-0.008	-0.01
	(0.009)	(0.013)	(0.015)	(0.016)
		B. Male		
Low Caste	-0.064	-0.094	0.031	0.105
	(0.084)	(0.051)*	(0.097)	(0.103)
Female	0.049	-0.001	0.056	0.03
	(0.055)	(0.034)	(0.064)	(0.068)
Age	0.009	0.001	0.008	0.007
	(0.014)	(0.008)	(0.016)	(0.017)
		C. Masters Degree		
Low Caste	-0.079	-0.09	0.011	-0.028
	(0.062)	(0.061)	(0.087)	(0.089)
Female	0.061	-0.033	0.093	0.127
	(0.041)	(0.040)	(0.057)	(0.059)**
Age	0.003	0.004	0	0.001
	(0.010)	(0.010)	(0.014)	(0.015)
		D. Below Median Age		
Low Caste	-0.135	-0.038	-0.099	-0.084
	(0.061)**	(0.062)	(0.087)	(0.092)
Female	0.061	-0.038	0.098	0.103
	(0.040)	(0.041)	(0.057)*	(0.061)*
Age	0	0.007	-0.007	-0.009
	(0.010)	(0.010)	(0.014)	(0.015)
Original Test Characteristics	YES	YES	YES	YES
Grader Fixed Effect	YES	YES	YES	YES

Note:

1. This table presents estimates of discrimination disaggregated by the characteristics of the teachers.
2. Each panel contains four sets of estimates. Estimates presented in column one are for tests graded only by teachers who have the characteristics indicated in the panel name. Column two contains estimates using only tests for teachers that do not have the indicated characteristic. Finally, column three presents an estimate of the coefficient on the interaction of the teacher's characteristic with the indicated observed child characteristics. Column four presents the same interaction but from a specification that includes interactions with the teacher characteristics from all of the panels.
3. The sample includes 3,000 graded exams (graded in sets of 25 by 120 teachers).
4. The outcome in every regression is the normalized total score.
5. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.

Appendix Table 1: Correlations between Original Characteristics and Final Test Scores

	Total	Total	Math	Hindi	Art
	(6)	(7)	(8)	(9)	(10)
Constant	-4.928	-0.929	-0.874	-1.021	-1.054
	(0.403)***	(0.165)***	(0.171)***	(0.193)***	(0.333)***
Kshatriya	-0.161	-0.012	0	-0.01	-0.083
	(0.042)***	(0.017)	(0.018)	(0.020)	(0.034)**
Vaishya	-0.516	-0.016	-0.033	0.003	-0.127
	(0.039)***	(0.016)	(0.017)**	(0.019)	(0.033)***
Shudra	-1.171	-0.012	-0.03	0.042	-0.176
	(0.068)***	(0.029)	(0.030)	(0.033)	(0.055)***
Unknown	-0.336	-0.009	-0.049	0.036	-0.106
	(0.045)***	(0.018)	(0.019)**	(0.021)*	(0.037)***
Female	0.213	-0.012	0.003	-0.002	0.007
	(0.028)***	(0.012)	(0.012)	(0.014)	(0.024)
Age	0.781	0.142	0.151	0.143	0.139
	(0.076)***	(0.031)***	(0.032)***	(0.037)***	(0.063)**
Age^2	-0.027	-0.006	-0.007	-0.006	-0.006
	(0.004)***	(0.001)***	(0.001)***	(0.002)***	(0.003)**
Blind Test Score		0.926	0.926	0.935	0.631
		(0.007)***	(0.007)***	(0.009)***	(0.014)***
Observations	3000	3000	3000	3000	3000
R-squared	0.34	0.89	0.9	0.85	0.5

Note:

1. This table contains the raw correlations between the grades awarded to the exams by teachers and the children's original, unobserved characteristics.

2. The first two columns contain results for the total test score, with and without controlling for the blind test scores. Columns 3 - 5 present the results, controlling for the blind test score, by exam section.

3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and *

Appendix Table 2: Randomization Check with Full Set of Caste Variables

	Actual Characteristics							Blind Scores			
	Brahmin	Kshatriya	Vaishya	Shudra	Unknown	Female	Age	Total	Math	Hindi	Art
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Kshatriya	0.041	-0.004	-0.039	0.024	-0.023	0.038	-0.199	-0.106	-0.093	-0.111	-0.062
	(0.028)	(0.032)	(0.035)	(0.017)	(0.028)	(0.036)	(0.150)	(0.072)	(0.072)	(0.072)	(0.072)
Vaishya	0.039	-0.026	-0.041	0.016	0.012	0.001	-0.079	-0.059	-0.056	-0.057	-0.035
	(0.022)*	(0.025)	(0.027)	(0.013)	(0.022)	(0.029)	(0.118)	(0.057)	(0.057)	(0.057)	(0.057)
Shudra	0.024	-0.027	0.009	0.007	-0.013	-0.001	0.01	-0.068	-0.061	-0.056	-0.087
	(0.025)	(0.027)	(0.030)	(0.015)	(0.024)	(0.031)	(0.129)	(0.063)	(0.063)	(0.062)	(0.063)
Female	0.02	-0.01	0.006	-0.009	-0.007	-0.021	-0.026	0.011	0.03	-0.002	-0.02
	(0.014)	(0.016)	(0.017)	(0.008)	(0.014)	(0.018)	(0.075)	(0.036)	(0.036)	(0.036)	(0.036)
Age	0.063	-0.034	0.053	-0.032	-0.05	-0.101	0.055	-0.013	0.046	-0.074	-0.005
	(0.045)	(0.050)	(0.055)	(0.027)	(0.045)	(0.058)*	(0.237)	(0.115)	(0.115)	(0.114)	(0.115)
Age^2	-0.003	0.002	-0.002	0.001	0.002	0.004	-0.003	0.001	-0.002	0.003	0
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)*	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000
F-Stat	1.38	0.47	1.41	1.06	0.95	1.08	0.61	0.4	0.5	0.48	0.83
P-Value	0.2184	0.8309	0.2084	0.3839	0.4613	0.3723	0.7212	0.8798	0.8106	0.8239	0.5469

Note:

1. This table contains regressions of the actual characteristics of the children on the characteristics randomly assigned to the coversheet of the exam that was graded by the teachers.

2. The F-statistic and p-value provide a test of joint significance of the observed characteristics.

3. Results that are statistically significant at the one, five, and ten percent levels are indicated by ***, **, and * respectively.