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Abstract

We address the challenge of designing performance-based incentive schemes for schoolteachers. When teachers specialize in different subjects in a society with social prejudice, performance-based pay that depends on the average of student performance can cause teachers to coordinate their effort on high status students. Laboratory experiments conducted in India with future teachers as subjects show that performance-based pay causes teachers to decrease effort in low caste Hindu students compared to upper caste Hindu or Muslim students. We observe greater effort and lower variation in an incentive design where teachers are penalized if students receive zero scores.

Keywords: Teacher incentives, Laboratory experiments, Coordination games, Discrimination.
JEL Codes: C92, I22, I28, J15.

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1 Introduction

Performance-linked salaries for teachers are a key element of many policies proposed to reform educational systems in both developing and developed countries. By tying pay to performance, as measured by achievement of students on tests, policy makers hope to align the teachers' self-interest with socially desired outcomes, motivating teachers to improve attendance, innovate on pedagogy and ensure student learning. In the United States, No Child Left Behind (NCLB 2001) mandates that students achieve federal standards in reading and mathematics, failing which schools incur a range of penalties, including loss of funding for teacher salaries. In developing countries such as India, teachers receive performance linked promotions and salaries in private schools, but not so in public schools that educate the vast majority of students. A number of field trials confirm that linking salary to student performance on external tests increases teacher effort in instruction, leading to improvements in students' scores. Lavy (2002) evaluates the fiscal efficacy of expenditures on teacher salary incentives compared to additional expenditures on teaching aids and finds that expenditures on the former are more effective. Glewwe, Ilias, and Kremer (2010) and Muralidharan and Sundararaman (2011) implement randomized field trials where the teacher's compensation is a linear function of the mean score of the students in the class, and find that financial incentives for teachers improve student test outcomes.

Although the link between incentive based pay and improvement in student test scores has been studied extensively, the literature does not sufficiently address distributional aspects of these incentives, in particular the potential for differential teacher effort in students that can cause unequal outcomes. A notable exception is Neal and Schanzenbach's (2010) study which reports that the design of the NCLB provides an incentive for schools to target students near the proficiency level for extra attention while ignoring students who are either clearly proficient or have little chance of becoming so. In addition, Neal and Schanzenbach (2010) show that inequality in teacher investments in students is partly conditioned on student identity, with Black and Hispanic boys recording the lowest improvement in scores. An incentive scheme might be economically inefficient if it directs teacher investment to those students who, on the margin, are unable to maximize the returns on this investment. This can happen if teacher investment is "misallocated" due to student identity, a concern valid in both the United States as well as developing countries that experience social stratification on the basis of group identity.

In this paper, we develop a theoretical model where the design of a hypothetical incentive pay program for teachers affects inequality in the classroom. We hypothesize that, in a multi-teacher environment with imperfect information, a salary that is a linear function of the average score of students in the class provides an incentive for teachers to coordinate their effort on a few students to maximize their payoff. Such an incentive can be the result of positive externalities in teaching two related subjects. For example, input from a Mathematics teacher can positively impact students' Science achievement, and vice versa. Insofar as teachers require a focal point for coordination, they might pick students' social identity, investing greater effort in teaching students with high social status and ignoring those with low status. We denote this mechanism "strategic discrimination". Thus, even if teachers are not prejudiced, pay based on student performance can cause sorting of student achievement on the basis of social identity as long as there is an expectation of prejudice by some teachers.

We test this hypothesis by conducting laboratory experiments in India using future teachers as participants. The use of laboratory methods offers several advantages over observational data or field experiments. First, experiments avoid endogenous selection of participants into treatment groups, a concern with studies using observational data. Second, an important variable of interest in this model, teachers' effort invested in students, is unobserved in data from surveys or field trials which does not allow conclusive identification of the mechanisms that cause poor distributional outcomes. Teachers' investment in students is observable in the laboratory, allowing the researcher to identify the particular behavior that impacts outcomes. Third, laboratory experiments are relatively inexpensive and quick to implement compared to large field trials, so multiple incentive designs can be tested at low cost. These limitations are overcome by conducting laboratory experiments with appropriate subject pools.

Field-based laboratory experiments show promise as a tool for shaping educational policy.[1] Hoff and Pandey (2006) conduct an experiment in rural India measuring the impact of revealed social identity on children's performance in educational games. They report that a history of caste-based prejudice implies that, once social identity is revealed, Scheduled Caste (SC) participants increase negative thoughts about themselves and are unwilling to bet on their own success. In parallel, they are not confident of fair treatment by the high-caste experimenters. Both these mechanisms lead to reduced effort and poorer outcomes on the educational games compared to their upper caste peers. Cadsby and Maynes (1998) and Ball and Cech (1996) show that the choice of subject pool affects the outcomes of policy-oriented experiments. These results motivate our decision to use participants who are enrolled in Bachelor of Education (B.Ed.) programs to prepare for careers as teachers.

One potential concern with laboratory experiments is the degree to which participant behavior is representative of field settings. Bauer, Chytilová, and Morduch (2008) compare survey data with data from field-based laboratory experiments conducted in three districts in rural India and report that patience and risk aversion measured by laboratory experiments predicts behavior in field settings. In the absence of similar studies with school teachers, we take a conservative approach while designing experiments and interpreting results. In particular, teacher student relationships and the sense of responsibility that develops from these human interactions are absent in the laboratory. Therefore, the participants of the laboratory experiment might simply be maximizing monetary returns, without regard to relationship considerations. At the same time, caste-based prejudice should also be lower in the laboratory, which would decrease the magnitude of the observed response. Hence, any results that we report from the lab ought to be interpreted as the lower bound to field based results.

India is a particularly appropriate setting for these experiments since the country is considering incentive-based pay for teachers in government-operated schools (Sixth Central Pay Commission 2008). Indian society also experiences widespread prejudice based on caste, religion and gender

[1] Harrison and List (2004) classify these as "artefactual field experiments".

(Govt. of India 2006), as well as significant differences in the educational achievements of upper caste Hindus compared to Scheduled Caste Hindus and Muslims (The PROBE Team 1999). Desai and Kulkarni (2008) find that 62 percent of children from upper caste Hindu and other religious groups (excluding Muslims) are likely to complete primary school, compared to 44 percent of Muslim children, 39 percent of SC children and 32 percent of Scheduled Tribe (ST) children. In addition, Hanna and Linden (2009) report that teachers discriminate on the basis of both caste and gender while marking exams, although they find that SC teachers discriminate against SC students.

In our experiments, participants are assigned the role of one among five subject teachers and have to choose which students to invest in under various incentive designs. We first test a fixed reward structure where the teacher's salary does not depend on student performance. This structure reflects the current compensation scheme for government school teachers. We expect that a payoff maximizing teacher will not invest much effort in her students under this scheme.[2] We then test a reward structure where a teacher's salary depends on the mean score of students in her class, incorporating variations with zero or positive returns to coordination. We expect greater discrimination on the basis of social identity in treatments with positive returns to coordination. Finally, we test a remedial treatment that helps mitigate outcomes for those students who would potentially not receive any investment from teachers.

The results of our experiments show that even with heterogenous student ability, teachers pick social identity as a focal point for coordination to maximize their earnings, disproportionately investing effort in upper caste and Muslim students at the expense of SC students. We calculate that the strategic discrimination mechanism imposes a penalty of 5 percent on the educational achievement of SC students. In addition, strategic discrimination is driven by upper caste teachers from urban backgrounds, with Scheduled Caste teachers coordinating on SC students. In the remedial treatment designed to penalize teachers if a student receives no attention, teachers distribute their effort more widely, suggesting a possible incentive design to escape the coordination trap.

The rest of the paper proceeds as follows. Section 2 develops a theoretical model of teacher

[2] Without any implications for gender roles, we use female pronouns for teachers and male pronouns for students throughout this paper.

investments in students with various incentive schemes. We describe the laboratory experiments methodology in Section 3 and analyze this data in Section 4. Finally, Section 5 concludes with discussion of the results and policy implications.

2 Theory

Our theoretical framework models how the incentive structure faced by teachers impacts inequality in student achievement. This model makes theoretical predictions that we test using data obtained from laboratory experiments. We model a multiple teacher classroom environment, similar to that in urban middle schools in India, with different teachers each specializing in a subject such as Science, Mathematics, Social Science, English and the local language. Further, we argue that the subject matter generates positive externalities from teacher effort. For example, if a Mathematics teacher offers assistance during office hours to a student, that investment impacts not only the student's understanding of Mathematics, but also his understanding of Science and other quantitative subjects. As a result, a student's achievement in a particular subject depends on the effort of all teachers. Koedel (2009) presents empirical support for such spillovers using data from the San Diego Unified School District in the United States. He shows that in addition to English teachers, the quality of Mathematics secondary school teachers influences reading scores. Specifically, a one standard deviation increase in Mathematics teacher quality increases reading scores by 0.06 standard deviations, a result that is statistically significant at the 1 percent level. Although we are unaware of similar studies set in developing countries, this evidence suggests that in multiple teacher environments, students experience returns to coordination in teacher investments.[3]

A second element of the theoretical framework is the perception of identity-based prejudice in society, i.e., there exists a social group such that at least some teachers believe that others will discriminate against the group. Such an assumption is justified in India which has a history of caste and religion-based discrimination (Deshpande 2006; Newman and Thorat 2007). At the

[3]Bruegmann and Jackson (2009) present a model where teachers learn from each other, which can be an additional externality.

same time, openly acknowledging such discrimination may carry stigma, so individuals might not perfectly know about the prejudices of their colleagues. Social discrimination is widespread in the education sector in India (Desai and Kulkarni 2008; Newman and Thorat 2007). Scheduled Caste and Muslim students experience significantly poorer educational outcomes compared to upper caste Hindu students (Govt. of India 2006). The PROBE Team (1999) conducted an extensive independent survey of education in India and attributed a part of these differences to the behavior of teachers in the classroom. The survey found that teachers ask Scheduled Caste students to run errands during class, neglect to focus on the developmental needs of students from these castes, and do not encourage such students to participate in classroom activities. Pandey (2005) suggested that teachers discriminate against low caste students by granting lower funds from what is supposed to be a mandated scholarship. Our model therefore focuses on the impact of social identity in teachers' decisions to invest in students.

A model of strategic discrimination adapted from Basu (2006) is the cornerstone of the theory. There are two elements that distinguish each student in our model - ability and caste. We assume that when pay is linked to student outcomes, student and teacher outcomes are increasing in student ability. We assume that caste is not correlated with innate ability, though the historical legacy of caste-based discrimination implies that caste is correlated with many inputs that students receive, such nutrition, healthcare, parental care and access to schooling which then translate into superior academic performance.[4] We show that even with this assumption, in the presence of caste-based prejudice, teachers might benefit from using caste for coordinating their investment when there are positive returns to such coordination, leading to better educational outcomes for upper caste students compared to lower caste ones.

In a society with pervasive caste-based prejudice, even an unbiased teacher might hypothesize that at least some of the other teachers are biased in favor of and might invest more in upper caste students. Therefore, even without significant difference in student ability, she will invest disproportionately in upper caste students to maximize her earnings if the earning increases in the average

[4]If we assume that caste, a form of social organization, is correlated with ability, then caste simply becomes a proxy for ability and we cannot identify the impact of caste on teacher behavior.

score of students and there are returns from coordinating with other teachers. If other teachers also hold the same beliefs, upper caste students will receive, on average, greater investments leading to better educational results and justifying the initial hypothesis. Thus, incentive design has the potential for sustaining social inequality in a multi-teacher setting even when not all individuals are necessarily prejudiced. An important feature of the strategic discrimination mechanism that distinguishes it from previous explanations of discriminatory behavior, such as the statistical discrimination model of Phelps (1972), is that it does not rely on either the student's exogenous ability or endogenous effort as the basis for unequal investments. The student's social identity is sufficient to generate discriminatory teacher behavior.[5]

The theoretical model specifies the payoff maximization problem that teachers face, and we solve this problem for optimal investment decisions made by teachers. We show the impact of these decisions on educational achievement for students, focusing particularly on inequality in outcomes within the classroom.

2.1 Model setup

In the theoretical model, students are indexed by $i \in \{1 : N\}$ and teachers are indexed by $j \in \{1 : J\}$. Students are of two observable types, A and B. The two types have the same distribution over ability, and are otherwise identical except that type B students are subject to prejudice by at least some segment of society. For simplicity, teacher j's investment of effort in student i is a binary choice $m_{ij} \in \{0, 1\}$. Thus, $\sum_j m_{ij}$ is the total investment received by student i from all teachers.[6] If a teacher decides not come to school, the decision is equivalent to choosing zero effort for all the students. Additionally, a teacher's total resources are constrained to $M_j < N$, which implies that she is not able to invest in all students.

How do teachers invest differently among students in the same classroom? Lectures might be

[5] Since strategic discrimination requires at least two teachers in a school, it does not predict discriminatory behavior in one-teacher schools that offer primary education in rural areas.

[6] Although we assume that the effect of investment is additive in the special case worked out in this section, the basic results do not hinge on this assumption.

tailored towards the needs, interests or level of understanding of some students in the classroom, excluding others. The teacher may encourage or address questions by some students and ignore others. Finally, the teacher may ask some students to run errands or sit outside the class in a space constrained environment. In addition, differential investment might imply that teachers may limit one-on-one time with certain students of the class. In our theoretical model, we simplify the idea of differential investment to be a binary decision of whether to invest or not invest in a student.

We propose a simple education production function where student i's educational output depends on his observed exogenous ability $\theta_i \in [0,1]$ and the number of teachers who invest in him $\sum_j m_{ij}$. For simplicity, we assume students' ability is common knowledge and accurately observed. Hence, we can write the composite educational output y_i for student i as

$$y_i = (1+\theta_i) f\left(\sum_j m_{ij}, J\right) \tag{1}$$

where $f(\cdot)$ has the following features:

$$f(0) = 0 \tag{2}$$

$$f(m+1) - f(m) > 0 \tag{3}$$

$$f(m+1) - f(m) \text{ is increasing in } m. \tag{4}$$

The first feature implies that students do not learn without teacher input. In other words, there are no "Einsteins" in our model. The second feature implies that student performance will improve if more teachers invest effort in that student. For instance, investment by two teachers will improve composite educational outcomes compared to a single teacher. The final feature is the supermodularity assumption which implies that the marginal impact of teacher investment is increasing in the amount of investment as a consequence of the returns to coordination by multiple teachers. Hence, the marginal impact of investment by a Physics teacher in a student who has already received training in Mathematics and Chemistry is greater than the marginal impact of the same investment in a student who has received training only in Chemistry.[7]

We assume that a teacher incurs a cost c each time she invests effort in a student. This cost represents the time and energy that the teacher expends in order to teach a student. For instance, the teacher's time spent during office hours can be viewed as an implicit cost incurred by the teacher. The costs could also represent the effort required to tailor class lectures towards the needs of a particular set of students or to provide one-on-one instruction. In reality, such costs are not necessarily constant or discrete, but assuming so offers considerable analytical simplicity without sacrificing insight into the problem. Thus, the total cost incurred by teacher j is

$$c_j = c \sum_i m_{ij} \tag{5}$$

Finally, a teacher can draw utility from her salary as well as other factors, a distinction that reflects that teachers are presumably more other-regarding than other kinds of professionals. Thus, a teacher's utility can be written as

$$u(x, \tau) \tag{6}$$

where x represents the salary earnings of the teacher, and is henceforth called the "payoff". τ represents other unobserved factors that add to the teacher's utility, for example, utility from having high achieving students, warm-glow utility from helping students learn (Andreoni 1990), or utility from undertaking actions associated with being a teacher (Akerlof and Kranton 2000).

The salary earnings for teachers and students are determined by the structure of the incentives offered to them. We vary this structure in order to model various incentive schemes while keeping everything else constant. This technique is valid if the utility from financial payoffs x is separable from the utility from other factors, τ. This allows us to present the teacher's problem

[7] Arguably, Science and Mathematics have stronger complementarities than English and Mathematics, but we abstract away from this. Further, we assume that learning Mathematics always increases the returns to a Science teacher's effort since Mathematics might help understand Science but does not substitute for understanding scientific concepts as such. Similarly, we assume that English instruction leads to greater returns for Science and Mathematics teachers by removing language barriers to understanding Mathematics and Science instruction. However, at no point does English instruction substitute for Math concepts.

simply as a matter of maximizing financial payoffs subject to constraints, instead of maximizing a composite utility function. The following sections show the theoretical variations and the resulting implications.

2.2 Impact of incentives

This section builds a formal model of teacher maximizing behavior in response to four different incentive designs. A summary of these designs is presented in Table 1.

A: A fixed salary that is independent of students' performance, less the cost of investment.

B: A salary that is a linear function of the average student score, less the cost of investment, with a student's score increasing *exponentially* in the number of teachers who invest effort in the student.

C: A salary that is a linear function of the average student score, less the cost of investment, with a student's score increasing *linearly* in the number of teachers who invest effort in the student.

D: A salary that is a linear function of the average student score multiplied by the fraction of students who receive better than zero payoff, less the cost of investment.

In what follows, we use the term "prejudice" to describe teachers' decisions to favor students of one type over another when, in the absence of returns to coordination, students of the first type are of equal or lower ability than the second.

$$Pr\left\{m_{ij}^{A} = 1\right\} > Pr\left\{m_{ij}^{B} = 1\right\} \text{ when } \theta^{A} \leq \theta^{B} \tag{7}$$

2.2.1 No incentive (A)

This section examines a teacher compensation scheme where the salary is independent of student performance. In this case, the teacher's problem can be written as

$$\max_{m_{1j}...m_{Nj}} \overline{p} - c \sum_i m_{ij} \text{ such that } N > M_j \geq \sum_i m_{ij} \tag{8}$$

where $\overline{p}$ is the fixed salary earned by the teacher and the constraint implies that the teacher cannot invest more than the resources available. Calculating the investment decision that yields the maximum payoff for the teacher is straightforward.

$$m_{1j} = ... = m_{Nj} = 0 \tag{9}$$

Thus, a teacher whose salary does not depend on students' performance but faces a cost every time she invests in a student ought not to invest in any student. With this result, the students' outcomes are

$$y_i = (1 + \theta_i) f(0) = 0 \text{ for all } i \tag{10}$$

from condition (2). Note that this result holds irrespective of student ability, θ_i. If we observe any teacher effort in students, we attribute this to other unobserved factors, τ_i, that impact teacher's utility. However, in the absence of such factors, a fixed salary offers no additional incentive to invest in students and yields poor outcomes from the perspective of a policy maker who wishes to improve educational achievement.

2.2.2 Teacher incentive with returns to coordination (B)

This section considers the impact of a teacher's salary that is equal to the average score of all the students in class when there are returns to coordination of teacher investments. As discussed earlier, we expect that the educational achievement of a student will be increasing in the number of teachers who invest in him because of positive spillovers from different academic subjects. So the teacher's payoff maximization problem is

$$\max_{m_{1j}\ldots m_{Nj}} \frac{\sum_i (1+\theta_i) f(\sum_j m_{ij}, J)}{N} - c\sum_i m_{ij} \text{ such that } N > M_j \geq \sum_i m_{ij} \tag{11}$$

and the supermodularity condition (4) holds. This condition implies that teachers have an incentive to coordinate their investments and invest in those students who also receive investments from other teachers. In a school environment, teachers might not have complete information on which students other teachers plan to invest in, or differential investment in students may not be openly discussed. Therefore, both student ability (teachers coordinating on high ability students) and social identity (teachers coordinating on students of a particular social group) are potential focal points for coordinating on students. Since both are observed in this model, we must carefully consider the interaction of identity and ability to determine which students the teachers invest in. Student ability has a direct impact on the payoff because the payoff is increasing in student ability. Therefore, teachers would always invest in high ability students and will not invest in students below a certain cut-off. When student ability is neither too high nor too low or when there are small differences in student ability, then teachers may coordinate on social identify. These cases are considered in detail below:

Case 1. $\theta_i > \theta^*$: This case considers investment in students with ability exceeding θ^*, which is defined such that

$$(1+\theta^*) f(1) \equiv c \tag{12}$$

Identity (12) implies that if a student's ability is high enough that investment by even a single teacher yields returns greater than cost, then teachers do not need to coordinate and would invest in him regardless of the other teachers' decisions. Since the problem is symmetric for all teachers, students with $\theta_i > \theta^*$ will receive investments from all J teachers and realize high educational outcomes.

$$y_i = (1 + \theta_i) f(J) \tag{13}$$

Case 2. $\theta_i < \theta^0$: This case considers investment in students with ability less than θ^0, which is defined such that

$$(1 + \theta^0)(f(J) - f(J-1)) \equiv c \tag{14}$$

A teacher's cost of investing in such a student exceeds the marginal return regardless of the investment decisions of the other teachers. So a teacher should not invest even if all other teachers decide to invest. Since the problem is the same for all teachers, no teachers will invest in students with $\theta_i < \theta^0$. As a result, the student's educational achievement will be zero, from condition (2).

Case 3. $\theta^0 < \theta_i < \theta^*$: Coordination is salient when a student's ability is not sufficient to determine the teacher's investment decision. In this case, teachers will realize greater payoffs when they select students who receive investment from other teachers as well. This problem is symmetric for all teachers, so coordination requires a focal point. When ability is neither too high nor too low and the difference in ability is not significant, with imperfect communication between teachers, social identity of the students offers a potential focal point. When students' type is observable in a society with pervasive prejudice, teachers might hypothesize that other teachers might discriminate against type B students. Then even an unprejudiced teacher who wishes to maximize her payoff should invest in type A students.

$$Pr\{m_{ij}^A = 1 | \theta^0 < \theta_i < \theta^*\} > Pr\{m_{ij}^B = 1 | \theta^0 < \theta_i < \theta^*\} \tag{15}$$

Since the problem is symmetric for all teachers, type A students will receive greater total investment

$$\sum_j m_{ij}^A > \sum_j m_{ij}^B \tag{16}$$

and realize better educational achievement compared to type B students.

$$y_i^A > y_i^B \tag{17}$$

Hence, the *ex ante* assumption that other teachers are biased against type B students will also hold *ex post*. Type B students will receive lower investments because of their social identity, a result that we term "strategic discrimination".

2.2.3 Teacher incentive with no returns to coordination (C)

This section models the teacher's maximization problem with no returns to multi-teacher coordination. This exercise is required because the strategic discrimination results modeled in the previous section rely critically on positive returns to coordination. Hence, to empirically identify the strategic discrimination model, we should compare the difference in teacher behavior with both positive and zero returns to coordination. The teacher maximizes her payoff as follows:

$$\max_{m_{1j}...m_{Nj}} \frac{\sum_i (1+\theta_i) f(\sum_j m_{ij}, J)}{N} - c \sum_i m_{ij} \text{ such that } M_j \geq \sum_i m_{ij} \tag{18}$$

Unlike the previous section, the supermodularity condition (4) does not hold, i.e., the student payoff is not increasing in the number of teachers that invest in the student. The problem is identical for all teachers with each teacher's decision independent of the others. Solving the maximization problem yields the optimal strategy of investing in the highest ability students. We can show that there exists a unique $\hat{\theta}$ with no returns to coordination in teacher investment such that

$$m_{ij} = \begin{cases} 1 & \text{for } \theta_i > \hat{\theta} \\ 0 & \text{for } \theta_i < \hat{\theta} \end{cases} \tag{19}$$

where $\hat{\theta}$ is such that

$$\sum_i (1+\hat{\theta}) f(\sum_j m_{ij}, J) = c \tag{20}$$

Hence, for a student with $\theta_i < \hat{\theta}$, the returns from investment are lower than the cost, and vice versa. Thus, teachers invest only in students above the threshold ability level $\hat{\theta}$. The average score of all students depends on the distribution of θ. If the number of students with $\theta > \hat{\theta}$ is less than M_j, the maximum amount of investment available to a teacher, then student achievement will be

$$y_i = \begin{cases} (1+\theta_i) f(J) & \text{for } \theta_i \geq \hat{\theta} \\ 0 & \text{for } \theta_i \leq \hat{\theta} \end{cases} \tag{21}$$

If the number of students with $\theta > \hat{\theta}$ is more than M_j, then teachers do not invest in some students with ability above the threshold. In the absence of prejudice, students achievement should not depend on the type.

$$Pr\left\{m_{ij}^A = 1\right\} = Pr\left\{m_{ij}^B = 1\right\} \text{ when } \theta^A = \theta^B \tag{22}$$

Type B students receive the same investment as type A students. Consequently,

$$y^A = y^B \tag{23}$$

and the educational performance of type B students is the same as type A students. Significant deviations from this result can be interpreted as reflecting preferences in favor of one type and against the other.

2.2.4 Remedial teacher incentive with returns to coordination (D)

This section examines a remedial incentive design where teacher salary is increasing in the average score of all students, but decreasing in the number of children who do not receive investments by any teacher and receive a score of zero.[8] In the previous section, we showed that teachers might strategically discriminate against students on the basis of social identity even if they are not themselves prejudiced. An incentive scheme that mitigates the effect of such discrimination should counter the need to coordinate on a specific set of students and instead distribute teacher effort equitably. In addition, the remedy must rely on easily and universally observed measures to gain acceptance among policy makers.

We consider a remedial design where teachers are penalized for completely ignoring a set of students.[9] The payoffs are declining in the proportion of students that receive no investment and have zero payoff. In practical terms, this remedial could imply that teacher salaries are adjusted downward depending on the number of students who fail, or receive grades less than a certain cut-off. The compensation formula thus includes the proportion of students who have investment from at least one teacher and therefore educational achievement greater than zero. Under this design, the teacher maximizes her payoff as follows:

$$\max_{m_{1j}\ldots m_{Nj}} \left[\sum_i (1+\theta_i) f(\sum_j m_{ij}, J)\right]\left[\frac{n}{N}\right] - c\sum_i m_{ij} \text{ such that } M_j \geq \sum_i m_{ij} \tag{24}$$

where n represents the number of students who have received at least one unit of investment and have positive payoff. When $\theta^0 < \theta_i < \theta^*$, teachers will realize greater payoffs by coordinating on a focal point while ensuring that all students get at least one unit of investment. If a non-zero subset of teachers prefers to invest in type A students over type B students, then the expected investment will be positive in type A students and zero in type B students.

However, each teacher has some incentive to deviate and invest in the highest ability type B student. Conversely, if every teacher invests type B students, each has some incentive to deviate and invest in type A students. This suggests a mixed strategy where teachers invest with positive probability in both type A and type B students, leading to positive educational achievement by all students.

[8] See condition (2).

[9] Carell, Sacerdote, and West (2011)'s study of peer effects at the US Air Force Academy has a similar objective function which was determined by the Academy's senior leadership.

3 Laboratory experiments

Empirical evaluation of the model in Section 2 requires a dataset that contains the distribution of teacher effort invested in students with and without performance-based pay. In addition, the dataset should measure the returns to coordination from investment by multiple teachers. The data should allow evaluation of alternative designs that address the shortcomings of currently proposed designs. Finally, the data should contain information on the teacher's demographic background as well as professional expectations and preferences on compensation structures.

Such data is difficult to obtain. The precise effort that a teacher invests in a student cannot be reliably reported, either by an external observer or through self-reporting. The financial and time costs of a large field trial of incentives for teachers is likely to require researchers to pick a single design. Finally, survey data does not allow us to experiment with different magnitudes of return to coordination from investment from multiple teachers.

Laboratory experiments, conducted with an appropriate subject population, can simulate the essential features of the classroom while evaluating the impact of teacher incentives on classroom dynamics. Additionally, experiments allow us to model and test a variety of alternative designs.

One possible criticism of using laboratory methods is that a list of names on a computer screen might not evoke the same response as a classroom setting, and that the responses would not reflect the complexities of human relationships, and the role they play in decision making. In our case, the concern is that the participants' decisions do not reflect teacher student relationships, and the sense of responsibility that develops from these human interactions. If this were true, the participants of the laboratory experiment results would maximize monetary returns, without regard to these real world considerations. At the same time, the participants would also disregard caste prejudice so that the bias in the laboratory would be to lower the magnitude of the observed response, so we should expect even stronger results in a field implementation of this study.

To test each variation of our model, we conducted experiments in the computer laboratory of Amity Institute of Education, a post-baccalaureate teacher training institute in New Delhi. Participants were enrolled in the Institute's Bachelor of Education (B.Ed.) program that prepares them for careers as school teachers. Their task was to distribute investments among a list of students (the "class") displayed on a computer screen.[10] Based on the investments by the teachers in each experiment, the resulting class performance was calculated and reported to the participant, along with earnings resulting from the incentive scheme under consideration. The following sections describe these laboratory experiments in more detail.

3.1 Experimental design

3.1.1 Parametrization of education production function

To calculate payoffs in the the experiments, we parameterized the educational production function presented in Section 2, where $f(\cdot)$ represents the returns from teacher investment in a student's academic performance. For this purpose, we use a straightforward functional form.

$$f\left(\sum_j m_{ij}, J\right) = \frac{\left(\sum_j \frac{m_{ij}}{b}\right)^{\alpha}}{J} \tag{25}$$

$\alpha > 1$ represents increasing and $\alpha = 1$ represents constant returns in the number of teachers who invest in student i. With this functional form, the returns to coordination increase as the positive spillovers between two academic subjects increase.

$$\frac{\partial f(\cdot)}{\partial \alpha} = f(\cdot) ln(\sum_j \frac{m_{ij}}{b}) > 0 \tag{26}$$

b is a fixed constant that helps to scale the students' score so that the expected payoffs are same in all treatments. With this parametric form and taking $\alpha = 1.1$, $b = 0.1911$, $J = 5$ and $c = 0.10$, we calculate the associated parameters for the minimum (θ^0) and maximum (θ^*) ability where strategic discrimination is salient.[11]

$$\theta^* = 0.684 \text{ and } \theta^0 = 0.316$$

[10]The experiment was programmed and conducted with the experiment software z-Tree (Fischbacher 2007).

[11]Taking $\alpha = 1.1$ approximates the estimate of teacher input spillovers from Koedel (2009). Selecting $J = 5$ reflects the number of teachers who teach a single set of students in many middle schools in India.

This choice of parameters ensures that the expected payoff in all four treatments is the same, and equal to Rs. 4 in each round.

3.1.2 Treatments

Table 1 describes the experimental treatments. Corresponding to the theoretical model in Section 2.2.1, Treatment A represents the fixed salary that teachers in government operated schools in India currently receive. The payoff for the teacher is the fixed salary, set at $\overline{p}$ = Rs. 4, less the number of students the teachers decide to invest in multiplied by the per student cost, c = Rs. 0.10.

In Treatment B, the teacher's compensation depends on the average performance of all the students in the class, with student performance benefiting from returns to coordination from teacher input ($\alpha = 1.1$), less the number of students the teachers decide to invest in multiplied by the per student cost, c = Rs. 0.10. In this treatment, modeled in Section 2.2.2, teachers can maximize their payoff by coordinating on the same students, either by coordinating on caste or on ability since these were the only two identity markers in the game. Within a similar range of ability, if teachers use caste and religious identity as a coordination device, we expect that teachers will invest disproportionately in upper caste Hindu students rather than Scheduled Caste or Muslim students.

The difference in observed total investment between Treatment A and B identifies the impact of the performance-based incentive program since the only difference between the two is the introduction of performance-linked salaries. Greater overall investment observed in B than in A indicates that teachers respond to the incentive. However, the difference in investments between Treatments A and B cannot identify the strategic discrimination model because the control for Treatment B should incorporate all reasons why teachers might prefer one student compared to another under performance-based incentives *except* the expectations of the other teachers' decisions and the associated returns from coordination.

Theoretically modeled in Section 2.2.3, Treatment C provides this control by modeling exactly the same reward structure as Treatment B, but removing the returns to coordination from the education production function, i.e., $\alpha = 1$, such that teachers have no incentive to coordinate their effort on a few students. Thus, an increase in concentration of investments in upper caste Hindu students and away from SC and Muslim ones in Treatment B compared to Treatment C identifies the strategic discrimination model.

Treatment D is a possible remedy that mitigates the impact of strategic discrimination. The incentive structure, specified in Section 2.2.4, is the same as Treatment B where the teacher's pay is increasing in the average performance of students in the class, except that we reduce the salary by the fraction of students who receive zero investments. Thus, we expect that teachers will distribute their investment more broadly among a greater number of students, which goes further in achieving the aims of the teacher incentive program.

We conducted the fixed-salary incentive (Treatment A) followed by the variable-salary incentives (Treatments B, C and D), reflecting the direction of the policy change. Thus, sequence effects are incorporated into the evaluation. With no obvious sequence for Treatments B, C and D, we conducted each sequence with an equal number of sessions.

3.2 Setup

3.2.1 Names experiment

For student identity in the experiments to matter, the participants must be able to associate names presented in the student list to a particular caste or religion. Attewell and Thorat (2007) and Banerjee, Bertrand, Datta, and Mullainathan (2008) show that employers in India are reliably able to distinguish between applicants from upper caste, Muslim and Scheduled Caste categories on the basis of their name.

We had 15 names in each experiment, with five names in each of the three caste categories: upper caste, Muslim and Scheduled Caste. To compile a list of names that is widely and accurately identified by caste and religion, we conducted a name recognition experiment. We obtained a list of 800 male names from a list of admitted students posted on the public website of Indraprastha University, that were classified as "General" (representing upper castes) or "Scheduled Caste" as required by statutes, and verified by reliable government processes.[12] We stripped this list of names of the category classification and instructed 10 students from a local college to indicate which category they believed each name belonged to. Muslim names were not included in the survey since there is very little uncertainty associated with them. The final list (see Table 2) was composed from 15 names that were 100 percent correctly identified in each category. The name list was used for all the experiments in our study for each of the five treatments, and the rounds within each of the treatments.

3.2.2 Subject recruiting

We recruited participants for our experiments from students enrolled in a Bachelors of Education program at a private educational institute in New Delhi. To select this site and subject pool, we wrote to all colleges in Delhi that offered certified B.Ed. programs. After follow-up phone calls, we selected Amity Institute of Education based on their availability and willingness to participate in the experiment. In addition, the institute offered the use of a computer laboratory where we could conduct the experiments. None of the participants had previously been a subject in an economics experiment. In all, we recruited 50 participants over two days of experiments.[13]

On arrival at the experimental site, participants completed the Informed Consent Agreement and received a participation fee of Rs. 20 in cash.[14] They were then randomly assigned to a treatment group and led to the computer laboratory. Once the experiments were complete, the participants completed a post-experiment survey and were paid their complete earnings in cash.

3.2.3 Experimental procedure

The experiment was conducted in five sessions, each lasting approximately two hours. In each session, ten participants were assigned to one of two independent groups.[15] Thus, in a group of

[12] The list was not generated by the researchers to prevent bias.

[13] The experiment took place on the first two days after enrollment into the program. Hence, while the participants are selected into the B.Ed. program, it is unlikely that they had significant knowledge about their peers, including each other's caste identity or caste preferences.

[14] The participation fee is \$0.42 based on an exchange rate of Rs. 47.54 per US Dollar on 11/08/2008.

[15] The computer laboratory had ten seats, which allowed us to accommodate two groups of five in each session.

five, every participant was randomly assigned the role of a subject teacher – either Hindi, Science, Social Science, Mathematics or English. At the beginning of each session, they were seated at a computer terminal and shown the game's instructions (Appendix A). These instructions were also delivered orally in English and then repeated in Hindi. Participants who did not know how to use a computer keyboard or mouse received a private demonstration from the experimenter. Matchings were fixed to mimic a school environment where the same teachers repeatedly teach the same students.[16]

Participants were told there would be multiple rounds in each of which they would choose how to distribute 8 units of investment among the 15 students, and that they incur a cost for each unit of investment made. Each participant was also informed of the structure of the returns from investment, which varied across the treatments. Participants were also informed that if none of the teachers invested in a student, the student would have zero educational outcome regardless of their ability, and that a higher ability student would have better educational outcome than a lower ability student for the same level of total investment by teachers.

Figure 1 shows the specific information available to each participant before she makes her decision. In each round, participants were shown the list of 15 students identified by an ID number and name.[17] Next to each student's name was a number that represented the student's intellectual ability. Ability was drawn from a distribution with mean 0.5 for the entire class, as well as for each sub-group by social identity (UC, SC and Muslim). Specifically, each sub-group of five names had one student with ability greater than 0.684 and one with less than 0.316, with three students with ability between 0.316 and 0.684. The mean ability for each sub-group was 0.5 and restricted between 0 and 1 for all the students in the class. The student's social identity was not explicitly stated but could be inferred from the student's name. Each participant's task was to choose whether to

[16]The Informed Consent Agreement clarified to each participant that the objective of the experiment was to conduct research that might inform policy, and that apart from the research paper, there were no other implications of the research outside the laboratory. In particular, no actual students would receive any educational benefits from the participants' actions in the experiment. Although these clarifications might impact behavior within the experiment, the bias is towards dampening investment and discriminatory behavior. Hence, our results are conservative lower bound estimates of teacher investment, discrimination and strategic discrimination.

[17]Each name was an identifiably male name to avoid gender effects.

invest costly effort in each student, picking at most eight students. Participants were not explicitly told the educational production function, but features specific to each treatment, such as increasing returns to coordination, were outlined in the instructions. The complete instructions for each treatment are in Appendix A.

In Section 2.2.2, we predicted that teachers could maximize their pecuniary payoffs by coordinating on a focal point. One possible concern was that participants might pick a focal point based on the position of the student name on the list. To prevent this, the order of names was randomized, and participants were informed that the order was unique to them.

Figure 2 shows the information available to each participant after she makes her decision. The participant sees a "report card" with her investment decision, the performance of all students on the list and her earnings for the round as feedback for subsequent rounds. Each participant could see only her own report card and earnings. The investment decisions of the other teachers were not displayed, but the number of investments in each student could possibly be inferred from the student's score. After a practice round, every treatment was repeated for 15 rounds so that participants would have sufficient time to learn about the nature of the payoff structure, as well as possibly find a focal point with other participants.

4 Empirical Analysis

In this section, we analyze the data generated from the laboratory experiments to evaluate the impact of a performance-linked teacher salary on classroom outcomes.

4.1 Data

We conducted four treatments, A-D as described above, of 15 rounds each with 10 groups of five participants each. Hence, the dataset contains 3,000 participant-round-treatment observations from a within-subjects experimental design.[18]

[18]Although the number of independent observations from 10 groups of 5 participants each is small, our test of theory is biased against finding a result. In case we find a result, more participants and groups are likely to provide additional

After the experiment, participants completed a demographic survey. Questions were framed to consider factors that might influence teachers' decisions to invest in their students, or possible prejudice towards social groups. Tables 3 and 4 describe the characteristics of the participants obtained from this survey. The sample is predominantly female (94 percent), which is not surprising since teaching is regarded in India as a profession more suitable for women. The sample includes a significant minority of SC participants (32 percent). Other variables attempt to capture the educational background of the participants, particularly their secondary school experiences, measuring the subjects they studied, the language of instruction and the type of school they attended. Table 3 suggests that the majority of participants are from Delhi which conditions both their prejudices as well as their expectations of other participants' prejudices, and hence the results should be extended to rural settings with caution.

The variables in Table 4 report the participants professional plans and preferences. Most participants plan careers as secondary school teachers (86 percent) suggesting this is an appropriate pool to test the multi-subject secondary school environment in our model. Participants' preferences for teaching different subjects seem to be evenly distributed between Science, Mathematics, Social Science and Languages.[19] Finally, participants were asked to state their preferences on different types of salary structures to gauge support for performance-linked incentives. Participants preferred a fixed salary (36 percent) to a salary that is based only on student achievement (14 percent), which suggests that implementing the latter might be practically difficult.

4.2 Results

Figures 3–6 describe teacher investments in students over 15 rounds for each treatment. Table 5 shows the same data in tabular form, along with averages for all rounds and the final five rounds where the participants are more likely to have discovered the equilibrium. In Treatment A, the optimal investment in students is zero since teachers receive a fixed salary with costly investment.

confirmation of the theory.

[19] We cannot distinguish between Science and Mathematics since they were combined together in the questionnaire.

Figure 3 shows that participants reduce their effort in students over the course of the session, investing in 6.64 out of 15 students in the first round, but 5.84 students in the final round.[20] Investment is 6.21 students per teacher averaging over all rounds, although this figure drops to 5.96 students if only the final five rounds are considered. Since teachers did not reduce their investments to zero to maximize their financial payoff, we conclude that other, unobserved factors such as altruism or a sense of professional duty have a large role in teacher investment decisions. Further, this result addresses the concern that a laboratory experiment would not reflect real world considerations, or that the participants are driven only by monetary rewards, since the instructions clearly indicated that the results of experiments will be used to inform policy and will not directly benefit any students directly.

Figures 4 and 5 describe teacher investments by round in Treatments B and C respectively. There is no clear trend over the rounds in these treatments, from which we infer that participants do not learn much over the various rounds. The overall level of investment is lower in Treatment B compared to Treatment A by 0.25, suggesting that performance-linked pay does not achieve it's overall goal of increased teacher effort. The difference in investment between treatments is 0.04 when only the final five rounds are considered.

Figure 6 shows the impact of the remedial treatment. Since the remedy encourages greater investment, the trend is steadily increasing from 6.10 students in the first round, to 6.56 in the last round, with an average of 6.33 over all rounds and 6.44 over the last five rounds.

The overall results are useful to understand the investment in students. However, as described in Section 3.1.1, teachers engage in strategic discrimination only within the ability range between 0.317 (θ^0) and 0.684 (θ^*). Table 6 reports the fraction of investment in each treatment that is allocated to students of UC, SC and Muslim backgrounds with this ability range. Surprisingly, within this ability range SC students receive the largest fraction of investments in Treatment A, without any incentive, as well as Treatment C, with incentive pay but no returns to coordination.

The difference in investments between Treatment B (with returns to coordination) and Treat-

[20]Recall that the maximum allowable investment was 8 students.

ment C (without returns to coordination) identifies the strategic discrimination effect. As predicted by equation 15, investments in SC students decline by 1.5 percent when coordination is salient in Treatment B, a difference that is statistically significant at the 5 percent level. Simultaneously, investments increase by 2.2 percent in Muslim students and decline by 0.6 percent in UC students, although neither change is statistically significant. Thus, increasing the returns from coordination leads to teachers decreasing their investments in low status Scheduled Caste students.

Although strategic discrimination against SC students is expected, Table 7 shows that Muslim students receive a higher than average level of investment in Treatment C, which increases in Treatment B, although the change is not statistically significant. This is a counter-intuitive observation, since Muslims experience social discrimination in India, and significantly lower educational achievement, especially in North and East India . One possible explanation is that Muslim educational achievement in the city of Delhi is above the average, unlike the situation in most parts of India (Govt. of India 2006).

To ensure that the results are robust to estimation approach, we also specify a probit model where the dependent variable is the decision ϕ_{ijkt} of participant j from group k to either invest or not invest effort in student i in her class during period t of the session.

$$\phi_{ijkt} = \begin{cases} 0 & \text{if } \phi^*_{ijkt} \leq 0 \\ 1 & \text{if } 0 < \phi^*_{ijkt} \end{cases} \tag{27}$$

ϕ^*_{ijkt} is a latent variable such that

$$\phi^*_{ijkt} = \sum_s \beta_1^s (I^s * ability_{ij}) + \sum_s \beta_2^s (I^s * \mathbf{identity}_{ij}) + \sum_s \beta_3^s (I^s * a_{ij} * \mathbf{identity}_{ij}) + \epsilon_{ijkt} \tag{28}$$

where $\mathbf{identity} = [Muslim, SC]'$. I is a dummy for each treatment where $s \in [A, B, C, D]$ represents Treatments A, B, C and D respectively. The variable $ability_{ijk}$ represents the student's ability drawn from a normal distribution with mean 0.5 and restricted between 0 and 1 for the entire class as well as for each sub-group by identity. a_{ij} is a dummy that indicates whether the student's ability is within the contested range defined in Section 3.1.1, i.e., between 0.316 and 0.684. The right-hand side of equation (28) includes group fixed effects, and the term representing unobservable characteristics, ϵ_{ijkt}, is clustered by period.

The main parameters of interest are β_3^B and β_3^C, which indicate the differential investment in Treatment B compared to Treatment C on the basis of identity for those students in the intermediate ability range. Thus, if the difference in parameters $(\beta_3^B - \beta_3^C)$ is negative, then a teacher's probability of investing in Muslim/SC students of intermediate range is lower in Treatment B compared Treatment C, which provides support for the strategic discrimination model predicted by equation (15).

Table 7 describes the results, which confirm the outcome from the non-parametric tests performed earlier. Participants coordinate away and reduce the probability of investing in SC students who are within the intermediate ability range by 3.1 percent when the returns from coordination are high in Treatment B. Additionally, strategic discrimination is specific to SC students in the intermediate ability range, is not observed in other students with either very high or very low ability. This confirms our expectation that strategic discrimination will increase the degree of discrimination faced by SC students.

Equation (23) predicts that strategic discrimination as a result of incentive design will increase the educational achievement of upper caste students compared to SC and Muslim students. Table 8 shows student achievement by treatment and group identity, with a separate column for achievement observed in the last five rounds of each treatment where convergence to equilibrium is more likely. These results are correlated with the teacher investment decisions but not a perfect mirror since heterogeneity in student ability is not considered in analyzing teacher investment.

As before, the difference between Treatment A and B shows the impact of performance-based pay for teachers, and the difference between Treatment B and C shows the specific impact of strategic discrimination on student achievement. Table 8 shows that student scores decrease by 0.16 points when the incentive is introduced, although the decrease is smaller (0.02) and statistically insignificant when only the last five rounds are taken into account. Thus, this laboratory experiment seems to suggest that changing the compensation scheme for teachers does not seem to have a significant impact on the outcome that policy-makers most care about, i.e., the educational performance of students.[21]

Conversely, the differences between Treatments B and C are large and statistically significant, both when considering all rounds, as well as just the final five rounds. Scores for the average student decline by 0.24 points going from 3.15 in Treatment C (incentive with no returns to coordination) to 2.90 in Treatment B (incentive with returns to coordination). The greatest decline is among Scheduled Caste students, who lose 0.34 points in educational achievement due to strategic discrimination. In contrast, Muslim and upper caste students lose 0.20 points as a result of introducing returns to coordination. When only the final five periods are considered, the decline in Muslim students performance mirrors the decline in Scheduled Caste performance. Thus, the difference in decline, approximately 0.14 points or 5 percent, is the educational penalty imposed by the strategic discrimination mechanism.

Tables 9 and 10 examine the behavior of participant sub-groups identified through the post-experiment survey. As noted in Section 4.1, questions on the post-experiment survey were framed to classify participants according to such criteria. An obvious category of investigation is the impact of a teacher's social identity as either an Upper or Scheduled Caste Hindu.[22] Table 9 suggests that strategic discrimination against SC students is driven by upper caste teachers. A UC teacher reduces investments in SC students by 3.4 percent in Treatment B compared to Treatment C. This result is reversed for SC teachers – an SC teacher increases investment in SC students by 2.3 percent while reducing it in UC students by 5.5 percent. However, since UC teachers form the majority of the participants in the experiment (68 percent), the average impact is strategic discrimination against SC students.

We propose three possible explanations for this result. First, SC teachers might have different

[21]These results should be read with the caveat that the measure of educational performance is derived from equation (1), which does not capture many other inputs that influence educational outcomes.

[22]None of the participants were Muslim.

expectations on coordination compared to UC teachers. They might be from backgrounds where the expectation is that other teachers will favor SC students and therefore strategically discriminate against UC students as a strategy to maximize earnings. Second, SC teachers might recognize that the UC majority will strategically discriminate against SC students when coordination is salient. To decrease the impact of this additional discrimination on students of their own community, SC teachers increase their investment in SC students. Third, Fehr, Hoff, and Kshetramade (2005) argue that spiteful preferences, which they define as the "desire to reduce another's material payoff for the mere purpose of increasing one's relative payoff" are widespread in the context of the Indian caste system. Thus, SC teachers might invest in Scheduled Caste students to reduce the earnings of UC teachers, despite receiving lower payoffs themselves, as a way to spite upper caste teachers. Without further analysis, however, it is difficult to determine which of these explanations accurately describes the results.

Apart from teacher's identity, we consider the potential for strategic discrimination based on other criteria that might influence teachers' decisions to invest in their students or possible prejudice towards social groups. Table 10 presents results based on whether the participant's origin, expressed by her parents' current residence, is from Delhi or outside.[23] We find that participants whose parents live in Delhi are likely to discriminate strategically against SC students (-2.4 percent and statistically significant at the 17 percent level) compared to participants whose parents live outside Delhi who do not (1.5 percent and statistically insignificant). Since these results are similar to the results in Table 9, we check whether residence in Delhi is correlated with UC status. The coefficient of correlation between social identity and residence is -0.098, which suggests that being upper caste is not correlated with origin from Delhi. Given this, one explanation for these results is that students from within Delhi may have more precise information about each others' prejudices, which allows them to coordinate away from SC students.

An additional variable of interest is the variance of teacher investments across rounds. Table 11 reports the fraction of students in each treatment who do not receive any investment as a measure

[23]In this sample, students whose parents live outside Delhi reported that they live in small towns and villages, not other metropolitan cities.

of the variance in investment. The fraction of students with no investment and hence variance in investment increases when incentives are introduced in Treatment B after Treatment A. This result confirms results from other experiments such as Bandiera, Barankay, and Rasul (2007) who report that introducing performance-based pay for managers who previously received fixed salaries induces greater variance in employee output. The results in Table 11 suggest that this is motivated by differential investment in students or employees by teachers or managers respectively. Finally, we confirm that the lowest variance in investment is observed in Treatment D, where teachers face a penalty for students who score nothing in educational output.

5 Discussion

Financial incentives for teachers to align their effort with the performance of the students they teach have drawn wide policy attention, particularly in developing countries. This paper examines the impact of such teacher incentives in an environment of widespread social prejudice. We show theoretically that in a multiple teacher setting common to secondary schools, an incentive where the teacher's salary depends on the average score of students, and student outcomes are increasing exponentially in total teacher effort, can lead to sorting of students on the basis of social identity. To confirm this theoretical prediction, we conduct laboratory experiments at a teacher training institute in India with future teachers as our subject pool. The results of our experiments show that even teachers who are not prejudiced might coordinate on social identity to maximize their earnings, a mechanism we term strategic discrimination. We find that such strategic discrimination is limited to SC students and does not extend to Muslim students, and is driven by upper caste teachers from Delhi. We conducted a remedial treatment designed to penalize teachers if students receive a zero score, and find that overall teacher investments were more widely distributed as a result.

Our results have implications for policy-makers who are considering teacher incentive programs. Insofar that sorting on the basis of social identity is driven by incentive design, policy-makers should rigorously test various designs for possibly pernicious effects. For this purpose, laboratory experiments using relevant subject pools can play an important role for testing different designs, and are particularly useful in revealing information that would not be observed in a field setting. Nonetheless, an obvious follow-up to the present study is a field experiment, which incorporates environmental factors that are missing in the lab.

The results should be read with a few caveats. First, these results are specific to a particular social situation. Prejudice as well as strategic discrimination against Muslims was significant in pilot experiments conducted in the Indian state of Gujarat, but not so in the main experiments conducted in Delhi.[24] Gujarat was the site of widespread violence targeting Muslims, which might cause teachers to think that the other teachers are prejudiced against Muslims. However, no corresponding violence occurred in Delhi which is a large cosmopolitan metropolis where prejudice against Muslims is less salient. This implies that policy-makers should account for local social conditions while designing teacher incentive programs.

Second, due to practical limitations, we could not incorporate two elements of classroom behavior that are also important for assessing the impact of teacher incentives. In these experiments, we assumed that student effort is exogenous in the classroom. Hoff and Pandey (2006) argue that students respond endogenously to perceived teacher behavior when social identity is salient. Hence, an important extension to the current set of treatments would be to allow students to simultaneously decide the level of effort that they invest in their studies. Another concern is teachers' decision to enter the profession might be influenced by incentives. If variable salary incentives are designed to have the same average payoff as a fixed salary, then higher ability teachers might enter the profession, and lower ability teachers might not. Insofar that the former have high capacity to invest in students, implementing teacher incentives can impact student outcomes on that basis. Evaluating such a scenario would require a two-step model of teacher selection and investment.

[24] Data from the pilot experiment is available upon request.

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Table 1: **Experimental treatments**

	Treatment	Return to coordination (α)	Cost of investment (c)	Financial payoff structure	Predicted investment
A	No incentive	1.1	0.1	Fixed salary less total cost of investment	No teacher investment
B	Incentive with returns to coordination	1.1	0.1	Average score of students less total cost of investment	Greater effort in high ability students and upper caste intermediate ability students
C	Incentive with no returns to coordination	1.0	0.1	Average score of students less total cost of investment	Greater effort in high ability students above a threshold
D	Remedial incentive	1.1	0.1	Average score multiplied by fraction greater than zero less cost of investment	Lower variance in investments across caste types

Table 2: **Student names used in experiment**

First Name	Last Name	Category
Surender	Bhokal	Scheduled Caste
Suraj	Kheeva	Scheduled Caste
Dharmsingh	Bairva	Scheduled Caste
Jaiprakash	Kirad	Scheduled Caste
Sham Lal	Nagah	Scheduled Caste
Anshuman	Shrivastava	Upper Caste
Abhijeet Kumar	Shukla	Upper Caste
Prabhakar Kumar	Mishra	Upper Caste
Vinayak	Dubey	Upper Caste
Aashish	Kapoor	Upper Caste
Mohd Aamir	Ansari	Muslim
Hidayat Ullah	Khan	Muslim
Mohd Salman	Siddiqi	Muslim
Abdul	Faisal	Muslim
Sadaf	Khan	Muslim

Notes: Names chosen were identified correctly by all participants in a survey, i.e., 100 percent correctly identified. All are ordinarily male names. Source: Names survey.

Figure 1: **Input screen for participants**

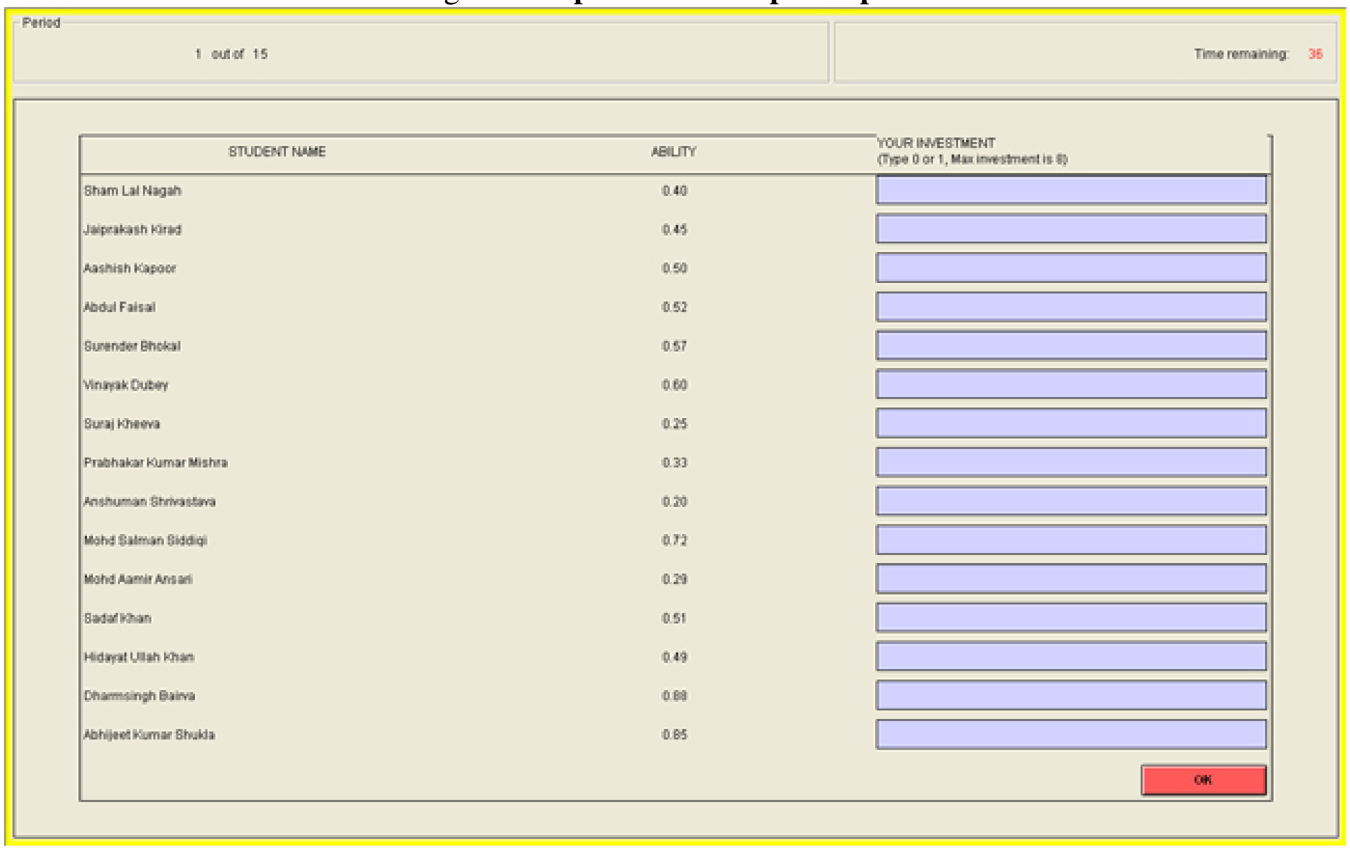


Figure 2: **Output screen for participants**

Period

1 out of 15

Time remaining: 16

STUDENT NAME	ABILITY	YOUR INVESTMENT	FINAL MARKS
Mohd Aamir Ansari	0.29	1	5.28
Prabhakar Kumar Mishra	0.33	1	3.97
Hidayat Ullah Khan	0.49	1	1.33
Vinayak Dubey	0.60	1	4.77
Surender Bhokal	0.57	1	8.22
Suraj Kheeva	0.25	1	3.73
Aashish Kapoor	0.50	1	4.48
Mohd Salman Siddiqi	0.72	1	3.28
Dharmsingh Bairva	0.88	0	1.68
Jaiprakash Kirad	0.45	0	2.77
Anshuman Shrivastava	0.20	0	2.29
Abhijeet Kumar Shukla	0.85	0	0.00
Sham Lal Nagah	0.40	0	2.67
Abdul Faisal	0.52	0	4.53
Sadaf Khan	0.51	0	1.35

Your income for this period (Rs.) 2.56

OK

Table 3: **Participant demographic characteristics**

Variable	Percent or Mean
Number of participants	50
Female	94%
Hindu	100%
Upper Caste	68%
Mother studied up to high school	56%
Mother working outside home	28%
Father schooling up to high school	28%
Parents live in Delhi	80%
Household income	
Less than Rs. 1 lakh per year	32%
Between Rs. 1 lakh and Rs. 3 lakh per year	42%
More than Rs. 3 lakh per year	26%
School attended	
Government school	56%
Private school	34%
Convent school	8%
Other	2%
School subjects	
Science	48%
Humanities	24%
Commerce	16%
Other	12%
Language of instruction	
English	66%
Hindi	34%

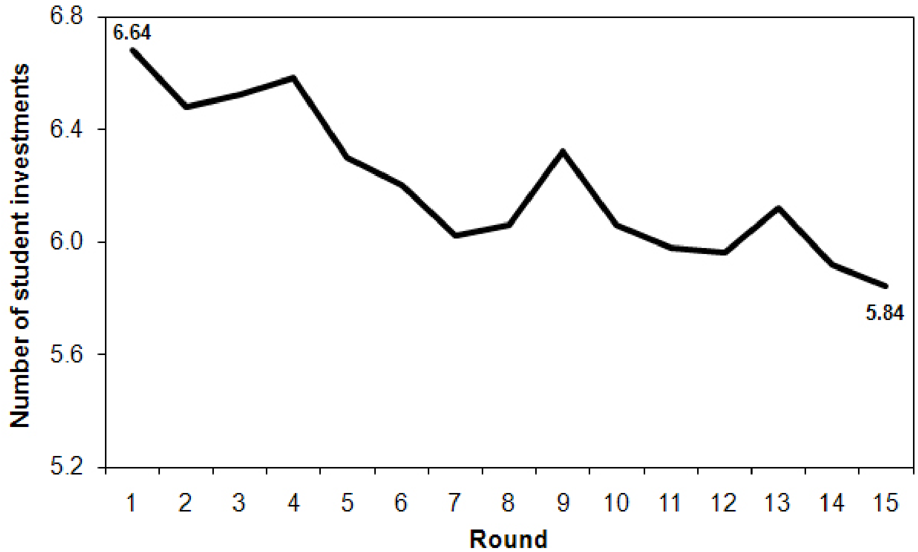
Notes: Rs. 47.54 = US$1 on 11/08/2008. 1 lakh = 100,000. *Government schools* are financed and managed by local government agencies such as the municipal corporation or village council. *Private schools* are financed and managed privately. *Convent schools* are financed privately and affiliated to Christian organizations. *School subjects* are specializations selected by students in grades 11 and 12. Source: Post-experiment survey.

Table 4: **Participant characteristics**

Variable	**Value**
No. of participants	50
Any teaching experience	22%
Any professional experience	26%
Future professional plans	
Teach in convent school	10%
Teach in government school	40%
Teach in private school	36%
Work in company	2%
Other work	2%
Study further	10%
Teaching first choice profession	90%
Grade teaching preference	
High school	48%
Middle school	38%
Primary school	8%
Nursery school	2%
No preference	4%
Subject teaching preference	
Science or Mathematics	44%
Social studies	22%
Language	26%
Other	4%
No preference	4%
Salary structure preference	
Earnings based completely on students' performance	14%
Earnings from fixed salary every month	36%
Earnings from lower salary plus a bonus	24%
No preference	26%

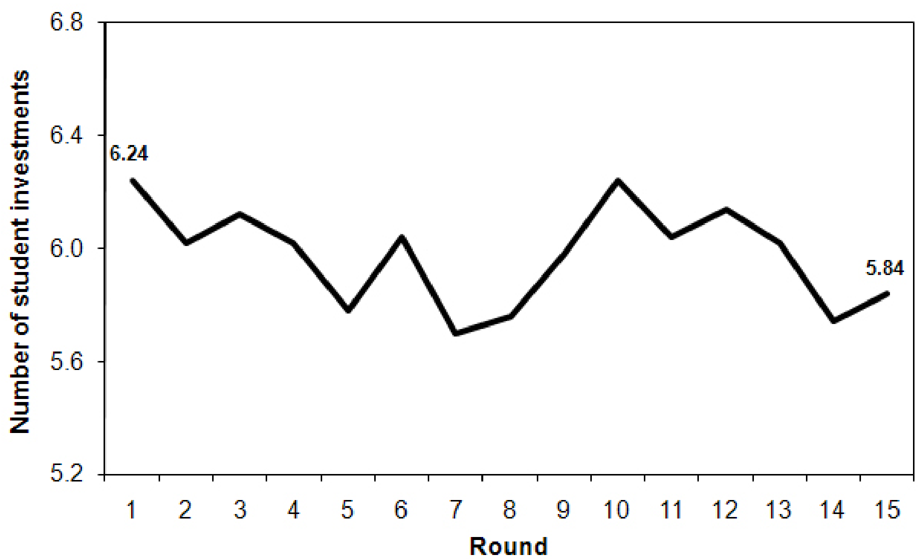
Notes: *Government schools* are financed and managed by local government agencies such as the municipal corporation or village council. *Private schools* are financed and managed privately. *Convent schools* are financed privately and affiliated to Christian organizations. Source: Post-experiment survey.

Figure 3: **Treatment A: Fixed salary**



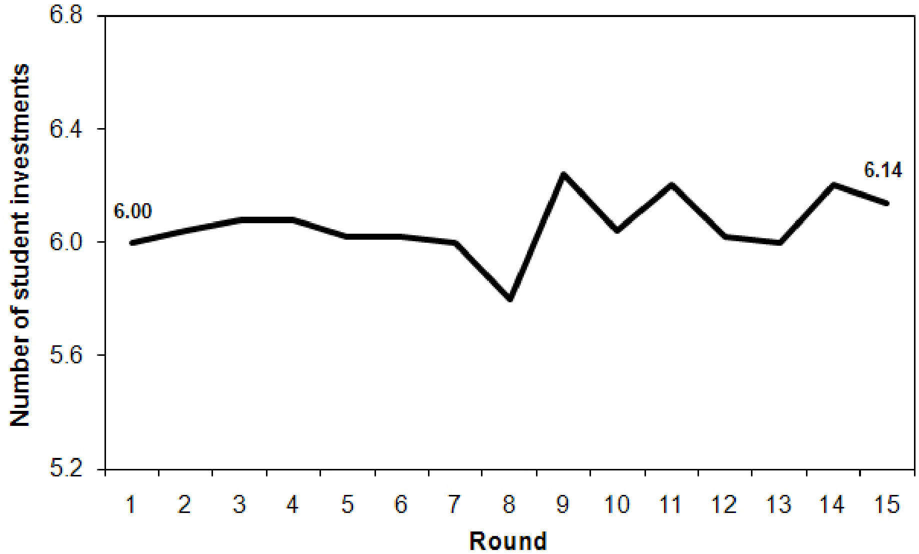
Source: Experimental data.

Figure 4: **Treatment B: Performance-linked incentive with returns to coordination**



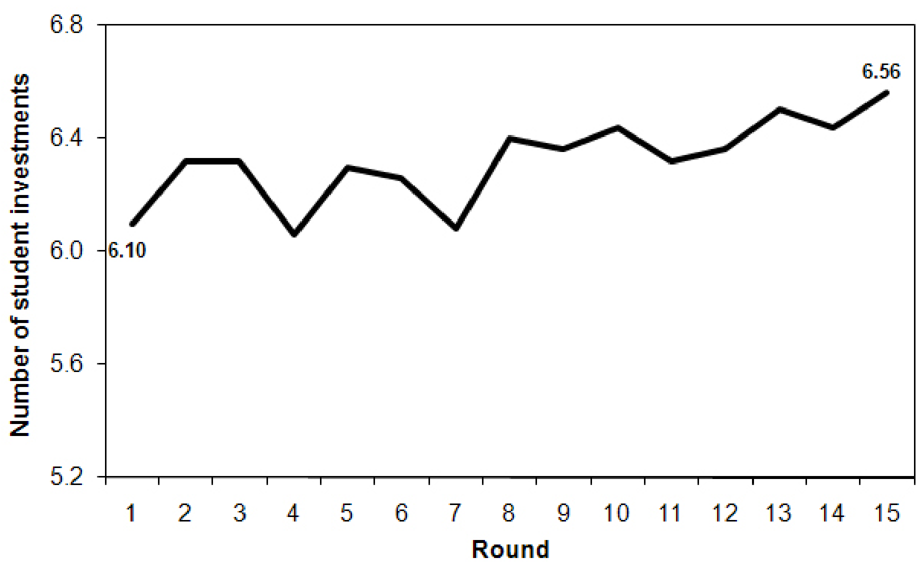
Source: Experimental data.

Figure 5: **Treatment C: Performance-linked incentive with no returns to coordination**



Source: Experimental data.

Figure 6: **Treatment D: Remedial incentive with returns to coordination**



Source: Experimental data.

Table 5: **Teacher effort by round**

Dependent variable: Teacher investment				
	Treatment			
Rounds	**A**	**B**	**C**	**D**
1	6.7	6.2	6.0	6.1
2	6.5	6.0	6.0	6.3
3	6.5	6.1	6.1	6.3
4	6.6	6.0	6.1	6.1
5	6.3	5.8	6.0	6.3
6	6.2	6.0	6.0	6.3
7	6.0	5.7	6.0	6.1
8	6.1	5.8	5.8	6.4
9	6.3	6.0	6.2	6.4
10	6.1	6.2	6.0	6.4
11	6.0	6.0	6.2	6.3
12	6.0	6.1	6.0	6.4
13	6.1	6.0	6.0	6.5
14	5.9	5.7	6.2	6.4
15	5.8	5.8	6.1	6.6
Average (All rounds)	6.21	5.96	6.05	6.33
Average (Final five rounds)	5.96	5.92	6.1	6.44

Source: Experimental data.

Table 6: **Results for strategic discrimination test**

Dependent variable: Fraction of total investment						
	Treatment					
	A	**B**	**C**	**D**	**Diff. between B and C**	**z-stat**
Muslim	0.320	0.349	0.327	0.320	+0.022	0.758
SC	0.344	0.339	0.354	0.352	**-0.015****	-2.351
UC	0.336	0.312	0.318	0.329	-0.006	-1.456

Notes: *Fraction of total investment* is the percentage of investments given to students of each type divided by the total investment in all students in the class. Results for students from intermediate ability range (0.316 – 0.684) where coordination is potentially significant. *SC* and *UC* indicate student is Scheduled Caste and Upper Caste respectively. Columns sum to one. z-stat and corresponding p-values reported from rank sum (Mann-Whitney) test of differences. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Source: Experimental data.

Table 7: **Probit results for strategic discrimination test**

Dependent variable: Investment decision			
	B	**C**	**Diff.**
Ability	-0.040	**-0.096*****	5.6%
	(0.025)	(0.018)	
Muslim	**0.051*****	**0.053*****	-0.2%
	(0.010)	(0.008)	(0.691)
Muslim x *a*	**-0.059*****	**-0.076*****	1.7%
	(0.015)	(0.010)	(0.340)
SC	**0.068*****	**0.066*****	0.2%
	(0.011)	(0.012)	(0.943)
SC x *a*	**-0.088*****	**-0.057*****	**-3.1%****
	(0.010)	(0.013)	(6.91)

Notes: *a* is an indicator variable indicating investment in intermediate ability group. *SC* indicates student is Scheduled Caste. Investment in Upper Caste names is the excluded category. Columns B and C report marginal effects computed from β_3^B and β_3^B respectively from equation (28). Estimation includes group fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. N = 11,250. Source: Experimental data.

Table 8: **Educational achievement**

	Dependent variable: Student scores							
	I: All periods				**II: Last five periods**			
	A	**B**	**C**	**D**	**A**	**B**	**C**	**D**
All students	3.06	2.90	3.15	3.10	2.91	2.89	3.17	3.15
	(0.53)	(0.54)	(0.55)	(0.48)	(0.57)	(0.57)	(0.51)	(0.49)
Muslim	2.98	2.91	3.10	2.99	2.84	2.86	3.18	3.05
	(0.74)	(0.74)	(0.70)	(0.66)	(0.71)	(0.80)	(0.67)	(0.67)
SC	3.12	2.96	3.30	3.20	3.05	2.99	3.32	3.17
	(0.72)	(0.73)	(0.73)	(0.71)	(0.56)	(0.57)	(0.46)	(0.46)
UC	3.09	2.84	3.04	3.11	2.83	2.81	3.01	3.22
	(0.73)	(0.81)	(0.77)	(0.76)	(0.78)	(0.82)	(0.76)	(0.74)

Notes: *SC* and *UC* indicate student is Scheduled Caste and Upper Caste respectively. Figures in parentheses are standard deviations. Source: Experimental data.

Table 9: **Impact of teacher's social identity**

Dependent variable: Fraction of total investment								
	SC teachers				**UC teachers**			
	B	**C**	**Diff.**	**z-stat**	**B**	**C**	**Diff.**	**z-stat**
Muslim	0.385	0.387	-0.002	-0.784	0.333	0.312	0.022	0.512
SC	0.370	0.323	0.047	0.633	0.325	0.359	**-0.034** ***	-2.811
UC	0.245	0.290	**-0.045** **	-2.362	0.341	0.329	0.012	-0.299

Notes: *Fraction of total investment* is the percentage of investments given to students of each type divided by the total investment in all students in the class. Results for students from intermediate ability range (0.316 – 0.684) where coordination is potentially significant. *SC* and *UC* indicate student is Scheduled Caste and Upper Caste respectively. Columns sum to one. z-stat and corresponding p-values reported from rank sum (Mann-Whitney) test of differences. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Source: Experimental data.

Table 10: **Impact of parents' residence in Delhi**

Dependent variable: Fraction of total investment								
	Teacher's parents reside in Delhi				**Teacher's parents reside outside Delhi**			
	B	**C**	**Diff.**	**z-stat**	**B**	**C**	**Diff.**	**z-stat**
Muslim	0.341	0.314	0.028	0.972	0.333	0.325	0.008	-0.216
SC	0.345	0.369	-0.024	-1.343	0.360	0.345	0.015	-0.653
UC	0.313	0.317	-0.004	-0.578	0.307	0.330	**-0.023***	-1.783

Notes: *Fraction of total investment* is the percentage of investments given to students of each type divided by the total investment in all students in the class. Results for students from intermediate ability range (0.316 – 0.684) where coordination is potentially significant. *SC* and *UC* indicate student is Scheduled Caste and Upper Caste respectively. Columns sum to one. z-stat and corresponding p-values reported from rank sum (Mann-Whitney) test of differences. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Source: Experimental data.

Table 11: **Variance in investment**

Dependent variable: Fraction with no investment				
	A	**B**	**C**	**D**
Muslim	7.6%	9.1%	8.2%	7.6%
SC	6.0%	8.4%	5.8%	5.8%
UC	10.2%	12.4%	10.9%	8.2%

Notes: Results for students from intermediate ability range (0.316 – 0.684) where coordination is potentially significant. *SC* and *UC* indicate student is Scheduled Caste and Upper Caste respectively. Source: Experimental data.

Appendices

A Instructions: Not for Publication

A.1 Instructions for Treatment A

Identity:

You have all been assigned roles as classroom teachers, each with different subject to teach. Your role will remain fixed throughout all rounds of the game.

Students:

You will be shown the list of students in your class with their names. All of you have the same students, though the order in which they appear on the list is different.

Task:

In this game, each of you will be asked to invest teaching effort among the students in your class. You can invest in either 8 students, or less than 8 students, but not more than 8 students. Note that this number is less than the number of students in your class.

Student Ability:

In front of each student there is a number between 0 and 1 that indicates each student's intellectual ability. The level of ability is increasing in the numbers, where 0 is the lowest ability and 1 is highest ability.

Investment:

Next to each student's name, there is a box. If you would like to invest in a student, type "1" in the box; otherwise type "0". The number of students you invest in must be less than or equal to the maximum number written on top. If you want, you can invest in fewer students than the maximum. However, the number of students you choose must not be more than the number written on the top of the sheet.

Student Performance:

The combination of the student's ability, whether or not you invest in a student, and whether or not other teachers invest in the student determines the student's final marks, based on the following rules:

1. If no teachers invest time in the student, regardless of the student's ability, the student will get zero

marks.

2. Otherwise, the student's marks will depend on their ability and the total number of teachers, including you, who invest teaching effort in the student. If more teachers invest in a student, then that student receives higher marks.

3. Moreover, the increase in student's marks is increasing in the number of teachers who decide to invest in a student. This means that the average marks of all students in the class will increase more if all the teachers focus their investments in a few students rather than distribute them among many students.

Rewards:

In each round, you will be paid Rs. 4, minus 10 paisa for each student you invest in. The students' final marks will have no impact on your earnings. Your earnings will be paid at the end of the game.

INSTRUCTION REVIEW

Identity:

You are a class teacher.

Task:

You have to invest in your students by typing 1 or 0 in the box next to the student's name. The maximum investment is 8. You can put in less effort, but not more, than 8.

Reward:

The combination student effort and the total number of teachers who invest effort in the student will determine the student's final marks. You will be paid Rs. 4 less 10 paisa for each student you decide to invest in.

If you have any questions, please raise your hand.

A.2 Instructions for Treatment B

Identity:

You have all been assigned roles as classroom teachers, each with different subject to teach. Your role will remain fixed throughout all rounds of the game.

Students:

You will be shown the list of students in your class with their names. All of you have the same students, though the order in which they appear on the list is different.

Task:

In this game, each of you will be asked to invest teaching effort among the students in your class. You can invest in either 8 students, or less than 8 students, but not more than 8 students. Note that this number is less than the number of students in your class.

Student Ability:

In front of each student there is a number between 0 and 1 that indicates each student's intellectual ability. The level of ability is increasing in the numbers, where 0 is the lowest ability and 1 is highest ability.

Investment:

Next to each student's name, there is a box. If you would like to invest in a student, type "1" in the box; otherwise type "0". The number of students you invest in must be less than or equal to the maximum number written on top. If you want, you can invest in fewer students than the maximum. However, the number of students you choose must not be more than the number written on the top of the sheet.

Student Performance:

The combination of the student's ability, whether or not you invest in a student, and whether or not other teachers invest in the student determines the student's final marks, based on the following rules:

1. If no teachers invest time in the student, regardless of the student's ability, the student will get zero marks.

2. Otherwise, the student's marks will depend on their ability and the total number of teachers, including you, who invest teaching effort in the student. If more teachers invest in a student, then that student receives higher marks.

3. Moreover, the increase in student's marks is increasing in the number of teachers who decide to invest in a student. This means that the average marks of all students in the class will increase more if all the teachers focus their investments in a few students rather than distribute them among many students.

Rewards:

In each round, you will be paid an amount equal to the average marks of all students in your class, less 10 paisa for each student you invest in. Your earnings will be paid at the end of the game.

INSTRUCTION REVIEW

Identity:

You are a class teacher.

Task:

You have to invest in your students by typing 1 or 0 in the box next to the student's name. The maximum investment is 8. You can put in less effort, but not more, than 8.

Reward:

The combination student ability and the total number of teachers who invest time in the student will determine the student's final marks. You will be paid an amount equal to the average marks of all your students, less 10 paisa for each student you decide to invest in.

If you have any questions, please raise your hand.

A.3 Instructions for Treatment C

Identity:

You have all been assigned roles as classroom teachers, each with different subject to teach. Your role will remain fixed throughout all rounds of the game.

Students:

You will be shown the list of students in your class with their names. All of you have the same students, though the order in which they appear on the list is different.

Task:

In this game, each of you will be asked to invest teaching effort among the students in your class. You can invest in either 8 students, or less than 8 students, but not more than 8 students. Note that this number is less than the number of students in your class.

Student Ability:

In front of each student there is a number between 0 and 1 that indicates each student's intellectual ability. The level of ability is increasing in the numbers, where 0 is the lowest ability and 1 is highest ability.

Investment:

Next to each student's name, there is a box. If you would like to invest in a student, type "1" in the box; otherwise type "0". The number of students you invest in must be less than or equal to the maximum number written on top. If you want, you can invest in fewer students than the maximum. However, the number of students you choose must not be more than the number written on the top of the sheet.

Student Performance:

The combination of the student's ability, whether or not you invest in a student, and whether or not other teachers invest in the student determines the student's final marks, based on the following rules:

1. If no teachers invest time in the student, regardless of the student's ability, the student will get zero marks.

2. Otherwise, the student's marks will depend on their ability and the total number of teachers, including you, who invest teaching effort in the student. If more teachers invest in a student, then that student receives higher marks.

3. Moreover, the increase in student's marks is in the same proportion as the number of teachers who decide to invest in a student. This means that the average marks of all students in the class will increase by the same amount if all the teachers focus their investments in a few students rather than distribute them among many students.

Rewards:

In each round, you will be paid an amount equal to the average marks of all students in your class, less 10 paisa for each student you invest in. Your earnings will be paid at the end of the game.

INSTRUCTION REVIEW

Identity:

You are a class teacher.

Task:

You have to invest in your students by typing 1 or 0 in the box next to the student's name. The maximum investment is 8. You can put in less effort, but not more, than 8.

Reward:

The combination student ability and the total number of teachers who invest time in the student will determine the student's final marks. You will be paid an amount equal to the average marks of all your students, less 10 paisa for each student you decide to invest in.

If you have any questions, please raise your hand.

A.4 Instructions for Treatment D

Identity:

You have all been assigned roles as classroom teachers, each with different subject to teach. Your role will remain fixed throughout all rounds of the game.

Students:

You will be shown the list of students in your class with their names. All of you have the same students, though the order in which they appear on the list is different.

Task:

In this game, each of you will be asked to invest teaching effort among the students in your class. You can invest in either 8 students, or less than 8 students, but not more than 8 students. Note that this number is less than the number of students in your class.

Student Ability:

In front of each student there is a number between 0 and 1 that indicates each student's intellectual ability. The level of ability is increasing in the numbers, where 0 is the lowest ability and 1 is highest ability.

Investment:

Next to each student's name, there is a box. If you would like to invest in a student, type "1" in the box; otherwise type "0". The number of students you invest in must be less than or equal to the maximum number written on top. If you want, you can invest in fewer students than the maximum. However, the number of students you choose must not be more than the number written on the top of the sheet.

Student Performance:

The combination of the student's ability, whether or not you invest in a student, and whether or not other teachers invest in the student determines the student's final marks, based on the following rules:

1. If no teachers invest time in the student, regardless of the student's ability, the student will get zero marks.

2. Otherwise, the student's marks will depend on their ability and the total number of teachers, including you, who invest teaching effort in the student. If more teachers invest in a student, then that student receives higher marks.

3. Moreover, the increase in student's marks is increasing in the number of teachers who decide to invest in a student. This means that the average marks of all students in the class will increase more if all the teachers focus their investments in a few students rather than distribute them among many students.

Rewards:

In each round, you will be paid an amount equal to the average marks of all students in your class times the fraction of students who receive more than zero marks, less 10 paisa for each student you invest in. Your earnings will be paid at the end of the game.

INSTRUCTION REVIEW

Identity:

You are a class teacher.

Task:

You have to invest in your students by typing 1 or 0 in the box next to the student's name. The maximum investment is 8. You can put in less effort, but not more, than 8.

Reward:

The combination student ability and the total number of teachers who invest time in the student will determine the student's final marks. You will be paid an amount equal to the average marks of all your students, less 10 paisa for each student you decide to invest in.

If you have any questions, please raise your hand.