Social distance and learning outcomes: evidence from Pakistan*

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October 29, 2013

Abstract

This paper provides the first evidence on the effects of caste on child learning outcomes in Pakistan. Using rich longitudinal data that allows me to convincingly identify the causal effects of caste, I identify the effects of child caste, teacher caste, and the interaction between child and teacher caste on children's test score outcomes. I show that particular combinations of high and low caste teachers and students are highly predictive of children's test score outcomes. Specifically, low caste male children perform significantly better when taught by high caste teachers than when they are taught by low caste teachers. These higher test scores are achieved by low caste boys working substantially harder: they spend 20% more time on homework when taught by high caste teachers. Several possible channels are explored, including discrimination in the classroom, role model effects, teacher quality, patronage, and returns to education. Although the channel cannot be proven, the results suggest that low caste children try to impress high caste teachers, either to prove themselves, or to potentially access the benefits of the high caste teachers' patronage networks in the future.

JEL Codes: I, I24, I25

1 Introduction

Inequalities in educational opportunities are characteristic of many low-income countries, and this hinders growth and development by limiting growth in human capital (Mankiw et al., 1992; Barro, 2000, 2001; Castelló and Doménech, 2002). These inequalities in education then also translate into inequalities in the labour market. In South Asia, inequalities exist not only in terms of wealth and income, but also between social groups. In particular, in both India and in Pakistan, caste is a primary determinant of both income and social inequality (Mohmand and Gazdar, 2007; Gazdar, 2007; Zacharias and Vakulabharanam, 2011). Understanding the role of caste-based inequalities in education and labour markets is critical to finding ways to reduce

*I thank Jishnu Das, Stefan Dercon, Robert Garlick, Paul Glewwe, Selim Guleci, Sonya Krutikov, Eliana La Ferrara, Andreas Madestam, Ghazala Mansuri, Albert Park, Simon Quinn, Kate Vyborny, and seminar participants at the Lahore School of Economics and the University of Oxford for helpful comments. This paper is produced as part of the project Actors, Markets, and Institutions in Developing Countries: A micro-empirical approach (AMID), a Marie Curie Initial Training Network (ITN) funded by the European Commission under its Seventh Framework Programme Contract Number 214705 PITN-GA-2008-214705.

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gaps, increase the stock of human capital, and promote growth in South Asia. This chapter aims to identify the role of caste in education in Pakistan.

Teacher labour markets and teacher assignment systems in public schools determine which students are taught by which teachers, and hence, the characteristics of teachers that students are exposed to. The question of whether, and which teacher characteristics matter for student learning has received extensive attention. It is important to examine learning outcomes, as these are what determine the skills that children will take to the labour market. Although teacher quality is considered integral to learning outcomes, there is no consensus on what makes a high quality teacher (Glewwe, 2002; Clotfelter et al., 2006; Glewwe and Kremer, 2006; Hanushek and Rivkin, 2006). A review of several recent studies in both the education and economics literature found that very few observable teacher characteristics contribute to learning (Glewwe et al., 2011). In the United States, studies have shown that the distribution of teachers' characteristics can affect student outcomes and can generate inequalities in learning (Rivkin et al., 2005; Hanushek and Rivkin, 2006; Jackson, 2009). In the United States, the black-white achievement gap has received substantial treatment in the literature, but elsewhere social distance has received less study. In particular, the issue of caste in South Asia is a recent contribution to the literature.

Previous work has shown that caste is an important determinant of enrolment decisions in both India (Dreze and Kingdon, 2001; Borooah and Iyer, 2005; Dostie and Jayaraman, 2006) and in Pakistan (Jacoby and Mansuri, 2011). In India, there is also growing evidence that caste is correlated with learning outcomes. There are a variety of reasons caste could affect learning, and it is not clear a priori whether there would be positive or negative effects, or both. There are three aspects to this: child caste, teacher caste, and the interaction between child and teacher caste. Child caste could be important if a school consists predominantly of either high or low caste children, and the other caste-type feels as if they are outsiders (Akerlof and Kranton, 2010). Alternatively, there may be differing returns to education for high and low caste children (Munshi and Rosenzweig, 2006; Luke and Munshi, 2007), or drawing attention to caste differences could affect children's confidence (Hoff and Pandey, 2006). Teacher caste could matter if high caste teachers are just higher quality teachers. The interaction between child and teacher caste could be important if either the same or different caste-type teachers can serve as role models to children (Kingdon and Rawal, 2010), or may discriminate against some children through biased grading practices (Hanna and Linden, 2012) or in the way in which they percieve children. Finally, since patronage in Pakistan is very closely tied to caste, it could also play a role in the education system and may even affect learning. Kingdon (1998) finds that conditional on enrolment, low caste children in India perform just as well as high caste children on cognitive tests. Unfortunately, there are no empirical studies in Pakistan of the effects of caste on learning outcomes, or of the impact of teacher caste on learning of students of different caste-types.

This paper aims to identify the effect of caste on children's learning outcomes. First, I look at whether learning outcomes of high and low caste children differ. I then investigate whether teacher caste affects children's learning outcomes overall, and finally, whether high and low caste teachers differentially affect the learning outcomes of high and low caste students. I use a detailed longitudinal study from Punjab, Pakistan, that tracks learning outcomes of the same children over four years. This allows me to identify teacher caste effects (as well as the interaction between teacher and child caste) using a child fixed effects specification, which ameliorates many concerns faced by studies attempting to identify the causal effects of teacher characteristics on student outcomes. In this case, the effect of a high caste teacher is identified from the same child switching between high and low caste teachers.

I find that in the cross-section, low caste children have higher test scores than high caste children. However, within schools there are no significant differences. Estimating the child fixed effects specification, I find that overall, having a high caste teacher has no impact on children's test scores. However, this result masks heterogeneity between caste types. I find that low caste children, and in particular low caste boys, have significantly higher test scores when they are taught by high caste teachers rather than by low caste teachers. This result is robust to the inclusion of many controls, as well as to tests that address the possibility of non-random switching of students to teachers. I find no significant differences in household characteristics between children who do and do not switch. So, it is the interaction between child and teacher caste that matters in Pakistan. In addition, low caste boys taught by high caste teachers spend almost an extra half hour per day doing homework. This is how the higher test scores are achieved.

Next, I investigate seven extensions and possible reasons that I find these results. Using data on the children's parents, I find that returns to education are high for low caste men. I also find that the positive effect of high caste teachers on low caste boys is stronger in the north of Punjab, where caste differences are more salient, than in the South of Punjab. One possibility then, is that low caste children work harder when taught by high caste teachers in order to overcome the stigma that is attached to lower caste groups. They may be trying harder in order to prove themselves, and especially so in areas where caste is more salient. Alternatively, high caste teachers may be able to help children gain access to employment and/or educational opportunities later on if they do well. In areas where caste is more salient, high caste teachers can be expected to have more influence. I do not find support for other mechanisms such as children feeling like outsiders, teacher quality, role model effects, or discrimination, as I exlpain in Section 5.

The next section will describe the history and meaning of caste, as well as the data used in this study. Section 3 will detail the ways in which caste could potentially affect learning outcomes. The empirical model to be tested is described in Section 4, followed by the results from estimating the empirical model in Section 5. Section 6 will conclude.

2 Caste and Education in Pakistan

The notion of caste in Pakistan is very different from that of India. Officially, caste does not exist in Pakistan, because caste is not recognised in Islam. However, people in rural Punjab are very cognizant of their caste group and that of others, and are also aware of the social conventions surrounding caste that have endured despite the official stance of the government. Several authors have noted its importance in relation to land ownership, employment, political disempowerment, health and education, and access to services (Gazdar, 2007; Mohmand and Gazdar, 2007; Jacoby and Mansuri, 2011).

In Pakistan, caste is a social, rather than a religious institution, and is interchangeable with clan, kin, and tribe (*zaat/biraderi*). Castes are based on 'lineage endogamy', with patrilineal cousin marriage forming the basis for the kin networks. A child inerits the caste of his/her father, so caste is fixed over generations. In addition, within each broad caste group there are sub-caste groups, and as is characteristic of endogamous kinship systems, men generally only marry women from the same sub-caste group within the broad caste group (Mohmand and Gazdar, 2007). These sub-castes are often associated with the region from which that particular sub-group originated. Many caste groups will live together in the same village, and schools will also contain a mix of high and low caste children (Andrabi et al., 2007).

Castes in Punjab are ranked according to historical land ownership and occupation. The hierarchy consists of land owners (*zamindars*), tenants/cultivators, service/artisan professions (such as weavers, iron smiths etc.), and finally outcaste groups (menial labour professions) (Ibbetson, 1974). Land owners and tenants are considered high caste, and service and menial labour professions are considered low caste. Within both the high and low caste categories, there is a range, with some castes considered to be of higher status than others. For example, the group '*Syed*' carries the highest status across Punjab, and other groups such as '*Jat*' and '*Rajput*' are considered of lower status than *Syeds*, but both are considered high caste, and which one is considered of higher status may differ by region and even by village. Here, I do not distinguish between the order of high and low caste groups, I distinguish only between those considered low caste and those not considered low caste. This is because a *Rajput* person will not treat a *Jat* person differently, but they may treat a low caste individual differently. Consequently, from now on any reference to 'caste' can be thought of as 'caste-type' (high or low).

People in a particular caste group tend to inherit the occupation of their predecessors. This is now becoming less prevalent as low caste groups are able to take up other professions, but still remains present. In Punjab, caste is closely connected to social status and dignity, and there is a large degree of social stereotyping, which is derogatory to lower caste groups. There are historical rules of social interaction that govern relationships between groups. For example, high caste groups will not eat with lower caste groups (Ibbetson, 1974). Furthermore, Mohmand and Gazdar (2007) conduct in-depth studies into the social structures and dimensions of social and economic exclusion in several villages across Punjab, and they find that in the North and Centre of Punjab, caste is a more salient factor in social interactions than it is in the South of Punjab.

Groups assume a corporate structure that performs political and economic functions (Mohmand

and Gazdar, 2007). In each village, each group vests authority in a leader who is responsible for organising economic exchanges and support mechanisms between members, and plays a key role in marriage decisions. However, members of lower caste groups often defer to leaders of higher caste groups for dispute resolution and economic support, as they are the resident landlords and are key sources of credit and patronage for their tenants and labourers (Mohmand and Gazdar, 2007). Vyborny and Chaudhury (2012) have also found that in Punjab, caste is important for patronage networks that can provide individuals and families with access to assistance in times of need as well as preferential access to services. Labour market opportunities are often mediated through social networks (Mohmand and Gazdar, 2007).

The data come from the Learning and Education Attainment in Punjab Schools (LEAPS) survey, which is an extensive longitudinal data set collected from 2003-2006. There are very few longitudinal studies in low-income countries that collect test score data as well as rich household level data that allows for the inclusion of many controls. 112 rural villages in the three districts of Attock (in the North of Punjab), Faisalabad (centre) and Rahim Yar Khan (south Punjab) were surveyed.

A detailed household survey was administered to 1,800 households that contained a child in grades 1 to 5. Many of the children in the household survey that were in grade 3 in 2003 were also tested as part of a concurrent school survey (an overlap of almost 1,200 children were administered both surveys and tests). Tests were administered in mathematics, English and Urdu (the official language in Pakistan). These tests were meant to be general, and a similar test was administered each year. The tests were scored using Item Response Theory (IRT) in order to make the tests comparable over time, and to measure underlying ability. IRT does this by estimating different weights to correctly answered questions depending on the difficulty of the question. The knowledge scores generated by this process represent a student's underlying knowledge in a particular subject. The knowledge scores are then converted into standard deviations from the mean for ease of interpretation. Teacher, and head teacher, and teacher tests in the same three subjects were also administered along with the school survey.

Both teachers and students are grouped into high and low caste groups, based on the caste reported by the household or teacher[1]. Whether caste group names are associated with land

[1] Cassan (2012) has noted that caste groups in Pakistan have manipulated their identity in the past. However,

ownership (high caste) or service professions (low caste) was determined by consulting two sources. The first was H. A. Rose's *A Glossary of the Tribes and Castes of Punjab and North-West Frontier Province*, which is the most extensive work detailing all castes in Punjab (Ibbetson and Maclagan, 1911). The second source was the District Gazetteers for the three districts in the sample, which were compiled by the British during the colonial era and include detailed descriptions of the occupations, customs, and land ownership of castes and sub-castes ((India), 1932, 1996; Dīn, 2001). Table 16 in the appendix lists the caste groups reported in the survey and whether they are classified as high or low caste.

Table 1 provides descriptive statistics of the 1,194 children in the sample, who are observed for between one and four years from 2003-2006 (2,642 child-year observations in total). High caste children make up 75% of the sample[2], and there are also more boys than girls (since these are all enrolled children by grade 3). High caste children tend to be enrolled in private school more than low caste children, and they also tended to still be enrolled in school several years after the survey (2011), and had completed more schooling. High caste households are much more likely to own land and have more assets, and parents are likely to be more educated.

Although there are differences in characteristics between high and low caste groups, there is also a substantial degree of overlap. Figure 1 plots the densities of some household characteristics for high and low caste households. There are more and less wealthy households, large and small families, and educated and uneducated fathers in both high and low caste groups, and both high and low caste groups own land. As a result, differences between high and low caste groups are not solely attributable to background characteristics, and more and less wealthy people in the same caste group will have similar social standing in the village (Mohmand and Gazdar, 2007).

Table 2 contains descriptive statistics on teachers in the sample by caste type. High caste teachers tend to be female, teaching in the same village that they are originally from, and more experienced. However, they tend to have lower levels of education than low caste teachers. Test scores of high and low caste teachers do not differ in any of the three subjects, nor are

in order for this type of manipulation to affect the results, it would need to be the case that households mis-report their caste in response to the switching of their child's teacher over the years of the survey. This is not the case in the data.

[2]This is in line with other studies, both in Pakistan and in India. In Pakistan, Jacoby and Mansuri (2011) also find that 75% of their sample of children is high caste. In India, Kingdon and Rawal (2010) find that 76% of students are 'high caste' (not Scheduled Caste or Scheduled Tribe).

there large differences in comparing absenteeism or time use for high and low caste teachers. Figure 2 shows the differences in test scores between high and low caste children, as well as the differences for high and low caste children taught by high and low caste teachers. The test scores of low caste children are higher than those of high caste children, regardless of whether they are taught by a high or low caste teacher. However, low caste children have higher test scores when taught by low caste teachers. If high caste teachers are not considerably different from low caste teachers in observable characteristics, but in the cross section low caste children appear to be performing better when taught by low caste teachers, this provides a justification to study the potentially differential effects of high and low caste teachers on high and low caste children in more detail.

Table 3 provides summary data on matches and switches between caste types of children and teachers. Panel A gives the number of male/female children of high/low caste-type matched with male/female teachers of high/low caste-type. Panel B provides the number of children who switch from a teacher of a certain caste/gender type to a teacher of either the same or a different caste/gender type. Panel C is simply Panel B in proportions. Public schools are segregated by gender, so gender matches are very common. If a child starts with a high caste teacher, he/she tends to stay with a high caste teacher. One point to note is that the number of switches of students between teachers of different caste types is very low. Out of 1,457 switches between teachers, only 120 are between teachers of different caste types. Only 3.2% of total switches (of the 1,457) between all teachers are from a high caste teacher to a low caste teacher. Switches from low caste teachers to high caste teachers are also relatively rare; only 5% of the total switches between all teachers in the sample.

In looking at child and teacher caste, an obvious concern would be non-random matching of teachers and students based on caste. In order to check whether the data resemble random matching of students and teachers, I perform two sets of tests based on Monte Carlo simulations. The aim is to test whether the composition of caste-type matches observed in the data resembles what we would observe if the matching of students and teachers were performed through random draws. Under the null hypothesis of random matching, the distribution of simulated matches approximates the actual distribution of matches. I look at this both within villages and within schools. Within villages, I randomly assign teachers to classes in the village in a particular year[3]. This takes the structure of each class as given and the number of classes within villages as given[4]. I can then calculate the frequencies of each of the four types of caste matches (teacher high caste, child high caste; teacher high caste, child low caste; teacher low caste, child high caste; teacher low caste, child low caste) in each village that is actually observed in the data and compare the observed matches to the matches from the simulated data in two ways. I first use the Chi-squared goodness of fit test for each village-year (314 village-years). I then conduct 314 Chi-squared tests to test the hypothesis that in the particular village and year, the distribution of the observed frequencies of matches is not too different from the distribution of the frequencies in the simulated data. Appendix Table 17 shows the means and standard deviations of the four categories of caste combinations with the observed and simulated data. In only 1.7% of the village-year cases (four village-years) is the Chi-squared p-value less than 0.05[5], suggesting that the data do resemble random matches of teachers and students. Figure 3 plots the distribution of the p-values from this test. It is not the case that the test is only just being rejected. The p-value is one in most village-years and there is no concentration of cases that only just pass the test. In the second test, I use the simulated matches to construct 95% confidence intervals for each of the four match types in each village and year. Table 4 reports the proportions of village-year cases for which the observed frequency in each category falls within the 95% confidence interval. This tests points to slightly less random looking data, especially for high caste children. 31% of village-years (97) do not fall within the confidence intervals in at least one category.

Within schools, I follow the same procedures but pool all years and randomly assign teachers to classes within the school[6]. I again calculate the observed frequencies of each of the four types of caste interactions and compare the observed matches to the matches from the simulated data. The Chi-squared goodness of fit test generates 266 Chi-squared test statistics that I use to test the hypothesis that in a particular school, the observed frequencies of matches are not

[3]I omit the fourth year of data because very few teachers were surveyed in the fourth round. Since the children were by then in middle school, only children who remained in primary school had their teachers interviewed in the fourth round. Random matching is performed 1,000 times.

[4]This is done because we cannot have third and sixth grade children in the same class, for example. In addition, the number of children in a class is then held constant.

[5]The average p-value is 0.8931 and the lowest p-value is 0.0032.

[6]I omit schools for which I have data on only one teacher. This leaves 266 schools within which children and teachers are randomly assigned to one another. The procedure amounts to asking, 'what if this teacher taught class x this year instead of last year'. This random matching is performed 1,000 times.

too different from the frequencies in the simulated data. For all 266 schools, the Chi-squared p-value is above 0.05[7], suggesting that the data does resemble random matches of teachers and students within schools. Figure 4 plots the distribution of p-values from this test, and here as well, it is not the case that schools are only just passing the test. The bottom panel of Table 4 reports the proportions of schools for which the observed frequency in each category falls within the 95% confidence interval. For all four categories, this proportion is above 85%, and for low caste children matched to both high and low caste teachers, the proportion of schools passing the test is above 90%. 41 schools (15%) fail the test in at least one category. That the observed matches in the data are not significantly different (according to two statistical tests) to randomly assigning teachers and students, indicates that although students were not randomly allocated to teachers in the sense of an experiment, the matching process of students and teachers is pseudo-random at least within schools.

As the next section will describe, caste does play a role in the education sector both in other South-Asian countries, and in Pakistan.

3 Why and how could caste affect learning?

This section provides a way to think about how caste might affect learning outcomes, and outlines how I will test for various mechanisms in the data. Caste-based stigma and discrimination is very much present in schools throughout South Asia, and there are many possible ways in which caste could affect children's learning outcomes. Three overall groups of channels can be envisaged: child caste, teacher caste, and the interaction between child and teacher caste. I will consider each group in turn, beginning with children's caste.

One potential mechanism is children's confidence. Hoff and Pandey (2006) have sixth and seventh graders in India solve mazes, and experimentally vary whether children's caste is announced publicly at the beginning of the test. When there are high and low caste children present and caste is announced, low caste children solve significantly fewer mazes than low caste children in the control group. The authors attribute this to lower confidence amongst low caste children when everyone is made aware that that they are of low caste. In sessions in

[7] The smallest p-value is 0.0834, and the average p-value is 0.983.

which there are only high/low caste children present and caste is announced, low caste children fare the same as those in the control group but high caste children solve significantly fewer mazes than high caste children in the control group. In the mixed groups, high caste children may want to distinguish themselves from low caste children and so want to perform better. In a second paper, the same experiment is conducted with tournament incentives instead of piece rate incentives, and the authors find that both high and low caste children solve more mazes under tournament incentives, but that revealing caste eliminates the positive effect of the tournament (Hoff and Pandey, 2011). These results illuminate the psychological aspect of caste, which can vary by caste-type and also by the composition of the groups present. Outside of such experiments, it would be very difficult to identify whether confidence is driving caste effects on learning outcomes, but I disaggregate between the three districts in Punjab, as caste differences are much more salient in the North than in the South.

These experiments also point to a potential effect of the distribution of caste groups in a school. The identity economics literature would argue that the key factor is whether the school creates an inclusive atmosphere (Akerlof and Kranton, 2010). Each school has its own ideals, shaped and enforced by the principal and teachers. These norms are often those of the predominant social group. The children who feel they do not fit these norms feel like 'outsiders' and tend to misbehave and not to perform well academically(Akerlof and Kranton, 2010). If a school is high caste dominant, low caste children may feel more like 'outsiders' and may have lower learning outcomes. I can test this mechanism by comparing differences between high and low caste children in schools comprised predominantly of high or low caste students.

Another mechanism that could affect learning outcomes is the returns to education. If high and low caste groups have differential returns to education, then we can expect that they would invest differently in human capital. Munshi and Rosenzweig (2006) study investments in education of children in South India. Exogenously increasing female income, they find that low caste families invest more in their children's education than high caste families, and that low caste children have significantly higher educational attainment than high caste children. Low caste households have fewer opportunities in the villages from which they originally come. Cutting ties with their traditional homes and instead investing in human capital of their children on the tea estate will bring them a higher return. In a companion paper, Luke and Munshi

(2007) find the same pattern for investments in the health of children. I will estimate earnings functions for high and low caste groups to provide insight into whether returns to education differ for high and low caste children in Punjab.

It is also possible that teacher caste could affect learning outcomes of students. In the simplest case, it could be that high caste teachers are just higher quality teachers than low caste teachers. Because of the history of exclusion of low caste groups in Pakistan, high caste groups could be more skilled and better trained. Alternatively, because of the obstacles facing them, it could be the case that the low caste individuals that do select into the teaching profession are of very high quality. Apart from better pedagogy, having a high quality teacher may also be motivating for students, and this could also result in higher test score outcomes. There could be observed and unobserved differences in quality. Observable differences can be controlled for in a regression framework. If high caste teachers improve the learning outcomes of all children, comparing children matched with high versus low caste teachers would tease out this effect. If high caste teachers do not equally affect high and low caste children, this would be evidence that it is not teacher quality that matters, but something else that affects only one group. In this case, unobserved differences in teacher quality can be differenced out by comparing high and low caste children in the same class.

Another possibility is that it is the interaction of child and teacher caste that affects learning outcomes. Studies in the United States and other high-income countries have found that children perform better when taught by teachers of the same race (Dee, 2005; Hanushek and Rivkin, 2006; Lindahl, 2007). These studies cite two possible mechanisms for how the interaction between teachers' and students' race could affect learning outcomes. The first is a role model effect. Minority teachers may inspire minority students by encouraging them to update their prior beliefs about their educational possibilities, and they may also feel more comfortable and more secure when taught by a person of their own race (Dee, 2005). Kingdon and Rawal (2010) find that students taught by teachers of the same caste status (low or high), gender, and religion, performed better in cognitive tests. They argue that this is because the teachers serve as role models to the children. According to these studies, if teachers are acting as role models, we would expect that children of a particular caste-type would perform better when taught by teachers of the same caste-type. Alternatively, it may be the case that teachers of a different caste-type could serve as role models to children. In this case, we would expect to see that children matched with teachers of the opposite caste-type have higher learning outcomes. However, finding this would not necessarily mean that children see teachers as role models. Data on whether a child wants to emulate his/her teacher by becoming a teacher later on, could also serve as a proxy for whether the child sees the teacher as a role model, and this is what I will use here.

Another aspect of caste that could differ between high and low caste children depending on whether they are taught by high or low caste teachers, was alluded to in the work done by Hoff and Pandey. In Pakistan, there is no reason to expect that the effects would be identical. It is possible that low caste children may have less confidence when surrounded by high caste peers and when caste is more salient, or that they also experience the 'stereotype threat'. However, it may also be possible that low caste children try to dispel myths about their caste type, and instead try to prove themselves by working hard and performing well in school. High caste teachers may also have more authority than low caste teachers, and this could be especially true when it comes to low caste children. High caste children in Pakistan may, instead of wanting to set themselves apart, not care to do so and this may also depend on peers and the teacher. These are passive effects of the interaction between teacher and child caste. Active mechanisms could also exist. Teachers may allocate more time and interact more with students who share the same racial or social background (Dee, 2005).

Another active mechanism that may differ by the interaction of teacher and student caste is discrimination. Discrimination could manifest itself in several ways. In Pakistan, Jacoby and Mansuri (2011) find that caste plays a role in the enrolment decisions of households. Children normally attend the closest school to their house that is grade and gender appropriate. However, they find that high caste girls are less likely to enrol in school if they have to cross a settlement boundary to get to school regardless of the distance, and that low caste boys and girls are less likely to enrol if the closest school is one in which high caste groups are dominant, due to social barriers and potential maltreatment from teachers. Another form of discrimination could be biased grading practices. Hanna and Linden (2012) conducted an experiment in India in which they randomly assigned child characteristics including age, grade, and caste to exams, which were then marked by a sample of teachers. They found that low caste children were scored between 0.03 and 0.09 standard deviations below high caste children, and that it was actually low caste teachers that were driving these results. Botelho et al. (2010) also find evidence for discrimination in grading amongst black children in Brazil. Lower grades will affect both progression through the schooling system and then labour market outcomes, and also confidence. In the case of Pakistan, it is not clear a priori who might be discriminating against whom. An experiment would be the ideal way to test for this type of discrimination. Discrimination could also manifest itself in the way in which teachers percieve a child. If a teacher dislikes a particular caste group, he/she may have a lower perception of the child's ability, and this could be a self-fulfilling prophecy for the child if the teacher either communicates this directly or indirectly, or if as a result, the teacher treats a child differently. I will use data on teacher perceptions of children, and compare this with children's actual ability.

Finally, there is another mechanism specific to the Pakistani context through which the interaction of child and teacher caste could affect learning outcomes. As noted in the previous section, labour market opportunities and social benefits are distributed in society by high caste individuals as favours to low caste individuals. Studies have pointed to patronage in the public sector for public goods in general, food aid, employment in the public sector, and government benefits (including in Pakistan) (Besley et al., 2004; Caeyers and Dercon, 2012; Fafchamps and Labonne, 2012; Vyborny and Chaudhury, 2012). If high caste teachers have the ability to distribute employment or educational benefits through patronage networks, then this might differentially affect the behaviour of high and low caste children in the classroom. High caste children would not necessarily need a high caste teacher's help but a low caste child would. For example, teachers may be able to help them gain formal sector (and in particular, public sector) employment after they finish school. They may also be able to help them get access to government scholarships, or to get admission into a good high school. In order to form a social network link with the teacher, the child's parents may become more involved in the child's schooling, or the child may work hard in order to impress the teacher. These efforts could lead to higher learning outcomes. Even though the child's entry into the labour market could be many years away, high caste teachers could still matter. The child and teacher most likely live in the same village, and the child and his/her parents could easily keep in touch with the teacher even if they do not since the teacher would come to the village for work every day. Public school teachers, and teachers in areas where caste is more salient would have a greater ability to distribute benefits to students.

All of these possible mechanisms may be at work here and this paper will be able to test for seven of them.

4 Testing for Caste Effects

In order to test the way in which child caste, teacher caste, and teacher-student caste interactions affect test score outcomes, I estimate an education production function of the form:

$$\begin{aligned} T_{ijst} = \beta_1 \boldsymbol{D_{ijst}} + \beta_2 \boldsymbol{XF_i} + \beta_3 \boldsymbol{XC_{it}} + \beta_4 \boldsymbol{XF_j} + \beta_5 \boldsymbol{XC_{jt}} + \beta_6 \boldsymbol{XF_s} + \\ \beta_7 \boldsymbol{XC_{st}} + t + \alpha_i + \alpha_j + \alpha_s + \epsilon_{ijts} \end{aligned} \tag{1}$$

where T_{ijst} is the test score of child i, taught by teacher j, in school s at time t. $\boldsymbol{D_{ijst}}$ represents the dummy variable(s) that will be included for child caste, or teacher caste, or for the interaction between teacher and student caste in the various specifications. $\boldsymbol{XF_i}$, $\boldsymbol{XF_j}$, and $\boldsymbol{XF_s}$ are fixed child, teacher and school observables, respectively. $\boldsymbol{XC_{it}}$, $\boldsymbol{XC_{jt}}$, and $\boldsymbol{XC_{st}}$ are time-variant child, teacher and school observables, respectively. t are time dummies, α_i, α_j and α_s are the child-specific, teacher-specific and school-specific time-invariant unobserved components, respectively, and ϵ_{ijts} is the error term.

Non-random matching of children and teachers to schools, and non-random matching of children and teachers to one another within schools, are the main threats to the validity of OLS estimation of equation (1). To address these issues, I employ a number of techniques to control for non-random sorting. As the Monte Carlo tests showed, sorting of teachers and children to one another based on caste is quite random within schools, but not always across schools. So at the very least, controlling for school fixed effects is important. As such, I estimate (1) first with school fixed effects, and then with child fixed effects, since there are multiple years of data available for each child.

With school fixed effects, the regression relates the difference between the child's test score in a particular year and the average of all children's test scores in all years at a particular school, to deviations of the child, teacher or school characteristics in one year from their average in all years at the same school:

$$(T_{ijst} - \overline{T}_{i,s}) = \beta_1(\boldsymbol{D_{ijst}} - \overline{\boldsymbol{D}}_s) + \beta_2(\boldsymbol{XF_i} - \overline{\boldsymbol{XF}}_{i,s}) + \beta_3(\boldsymbol{XC_{it}} - \overline{\boldsymbol{XC}}_{i,s}) + \beta_4(\boldsymbol{XF_j} - \overline{\boldsymbol{XF}}_{j,s})$$
$$+ \beta_5(\boldsymbol{XC_{jt}} - \overline{\boldsymbol{XC}}_{j,s}) + t + (\alpha_i - \overline{\alpha}_{i,s}) + (\alpha_j - \overline{\alpha}_{j,s}) + (\epsilon_{ijst} - \overline{\epsilon}_s) \tag{2}$$

Any time-invariant school-level observed ($\boldsymbol{XF_s}$) and unobserved (α_s) factors are swept away since they are common to all students and do not change over time. Sorting of children and teachers to schools now will not bias the results. However, time-invariant unobserved child and teacher factors (α_i and α_j) remain as deviations from the average at the school. Any sorting of children to teachers within schools due to unobserved time-invariant factors that are correlated with caste, will bias β_1. The results of the Monte Carlo simulation-based tests in the previous section suggest that caste-based matching of teachers and students within schools is not occurring, but I include measures to correct for it anyway.

One potential difficulty is the existence of multiple classes within each grade. If schools organise either advanced or remedial classes, and teachers are allocated to them in a manner related to caste, this will also create bias in the estimated coefficient. In Punjab, this concern is ameliorated because most schools have only one class per grade. Another potential difficulty is non-random matching across grades. For example, schools may place high quality, high caste teachers in higher grades and high and low caste students that perform well will get promoted to these grades. Schools could alternatively have a policy of matching high quality teachers to low ability cohorts, for example. It is also possible that teachers and children (or parents) can lobby for reshuffling of teachers within schools based on teacher characteristics that they prefer, including caste, or they may strategically time enrolment or arrange for their children to skip grades or be held back. Any type of positive sorting within schools (high quality teachers matching to high quality students) would overestimate the effect of teachers. For children, within schools, any non-random sorting would have to be due to assignment to grades in the absence of multiple classes per grade. As a result, I include grade dummies, as well as the child's age and a dummy variable for whether the child was held back in the grade. This will control for differential age at enrolment, grade assignment and non-promotion based on caste. The grade dummies also control for the possibility of high caste teachers being allocated to higher grades, as long as any non-random sorting of teachers across grades is common across schools.

In addition, school fixed effects do not control for children or teachers switching schools[8]. If low caste children that perform well switch to a better school, or to a school with more high caste teachers, then this will overestimate the effect of high caste teachers. There are nine cases in which the switch between high and low caste teachers is because of switching schools (6.9% of total switches between high and low caste teachers)[9]. I omit these observations from the analysis. I also check whether teachers match to schools based on caste. Not all teachers in a school were surveyed, but the sample of teachers surveyed in each school is random. A regression of a dummy variable for a high caste teacher on over fifty school controls produces only six significant correlates (four at the 10% level, one at the 5% level, and one at the 1% level, see Appendix Table 18). This finding further alleviates concerns of unobserved teacher factors influencing caste-based matching to schools.

Child fixed effects estimation can control for non-random sorting of children within schools. Such estimation relates the difference between a child's test score in year t and the average test scores of the child over all years, to the deviation of the child, teacher or school characteristics of the child in time t from the average for the child in all years:

$$\begin{aligned}(T_{ijst} - \overline{T}_i) &= \beta_1(\boldsymbol{D_{ijst}} - \overline{\boldsymbol{D}}_i) + \beta_2(\boldsymbol{XC_{it}} - \overline{\boldsymbol{XC}}_i) + \beta_3(\boldsymbol{XF_j} - \overline{\boldsymbol{XF}}_{j,i}) \\ &+ \beta_4(\boldsymbol{XC_{jt}} - \overline{\boldsymbol{XC}}_{j,i}) + t + (\alpha_j - \overline{\alpha}_{j,i}) + (\epsilon_{ijst} - \overline{\epsilon}_i)\end{aligned} \tag{3}$$

Now, time-invariant observed and unobserved child factors also drop out. With child fixed effects, non-random switches between high and low caste teachers is the concern. A key assumption for child fixed effects to be valid is that past error terms are not correlated with the switching of teachers. For example, if children that perform better (or worse) last year switch to high caste teachers, this would be a problem. As a result, I run a regression of switching between high and low caste teachers on lagged test scores, as well as many other controls. The results are contained in Appendix Table 19. Lagged test scores do not predict switching between high and low caste teachers, however, lagged test scores can be included in the regressions. In

[8]Only 2.6% of children in the sample switch schools between rounds, and only 2.7% of teachers switch schools between rounds.

[9]The results are also robust to omitting all children that switch schools (70), regardless of whether they switched caste-type of teachers.

addition, the child-level and household-level variables do not predict whether a child will switch between caste types of teachers. So it does not appear as if the children who do switch are different from those who do not switch. Child fixed effects also requires that unobserved inputs such as motivation, preferences for an own caste-type (or opposite caste-type) teacher, and any others, be constant over time and not affect switching of teachers. Finally, the fixed effect (for example, child ability) also must be constant over time for child fixed effects to difference it out.

I will begin by estimating a regression of average test scores on a dummy variable (D) for being a high caste child. This specification will identify the effect of child caste on learning outcomes. This effect can be identified only with school fixed effects, of course. I will also add to this specification a dummy variable for having a high caste teacher in that year. The dummy variable for having a high caste teacher can be identified with both school and child fixed effects, but I will identify the effect of teacher caste mainly through child fixed effects regressions. Identification here is off the same child switching between high and low caste teachers.

Then, I will look at differential effects by caste-type of the child. Here as well, I will use both school and child fixed effects. Within schools there are four possible matches of high/low caste students and teachers. In the specifications with school fixed effects, the dummy variables included in $\boldsymbol{D}$ are:

- child high caste, teacher high caste;
- child high caste, teacher low caste; and,
- child low caste, teacher high caste.

The coefficients on these dummies represent the effect of that particular match relative to the omitted category of low caste students matched with low caste teachers. In the specifications with child fixed effects, the dummies included in $\boldsymbol{D}$ are:

- child high caste, teacher high caste; and,
- child low caste, teacher high caste.

Since this is a within-child specification and a child can only be either high or low caste, we can only include two dummy variables, and the coefficients represent, for that particular caste-type of child, the effect of being taught by a high caste teacher relative to being taught by a low caste teacher. Identification of the two variables is off children who switch between high and low caste teachers over time.

Non-random attrition in the sample could bias coefficient estimates. If the lowest ability low caste children drop out of school, then the remaining ones will induce positive matching of teachers and students by caste (within schools). Most children are observed in at least three rounds of the survey, and there are no significant differences between high and low caste children. See Table 20 in the appendix for details.

Another potential concern is that caste may be proxying for other characteristics. Consequently, I control for some child and household-level characteristics that could be correlated with caste. As child controls I include the age of the child, a dummy for whether the child is female (in the school fixed effects specifications), a household asset index, dummies for the grade level of the child, a dummy for whether the child is repeating the grade, a dummy for each parent being uneducated, and household size [10]. High and low caste teachers may also differ systematically in their observable and unobservable characteristics, and so it is important to control for observable characteristics. I will also employ methods in the next section to address unobservable characteristics. As teacher controls I include the teacher's age, number of years of teaching experience, dummies for the highest level of education, and dummies for whether the teacher is female and is originally from the same village in which the school is located. As school controls I include the number of children enrolled in the school, and a school facilities index[11]. Finally, time dummies are included to control for the fact that children tend to perform better on the test over time.

5 Results

This section will discuss the results of estimating the empirical models presented in the previous section. I will begin with identifying the effects of child caste, teacher caste, and the interaction

[10]There is some missing data on parental education. For those cases, I include a missing data dummy.

[11]This index is constructed from a number of questions on the survey that ask about whether the school has the following facilities: library, computer, sports ground, hall, surrounding wall, fans, electricity, the type of toilet, whether potable water is available, and the seating arrangements for students (desks, mats, etc.). Principal Components Analysis was used to aggregate these measures.

of teacher caste with student caste, and then will look into some potential mechanisms by which the findings could be occurring.

5.1 Child caste, teacher caste, and the interaction between child and teacher caste

Table 5 presents basic results on the effect of child caste, as well as the effect of high caste teachers on all children. The outcome is the average of math, English and Urdu test scores for each child. Columns (1)-(3) present school fixed effects results. A dummy variable for high caste children is included, as is a dummy variable for a high caste teacher. Column (1) does not include controls and thus provides a basic correlation, column (2) adds child, teacher and student controls (equation (2)). Column (3) adds the lagged test score to the right hand side to control for past learning. It is meant to capture the contribution of all previous inputs and any past unobservable endowments or shocks, and is becoming increasingly common to include in test score specifications (Todd and Wolpin, 2007; Andrabi et al., 2011). Here, one could also worry that children are being matched to high/low caste teachers based on their previous test scores (for example, if children performing poorly were placed with high caste, high quality teachers). Columns (4)-(6) present child fixed effects results, which identify only teacher caste effects (as child caste is time-invariant and drops out). Column (4) once again has no controls. Column (5) adds child, teacher and school controls (equation (3)). Column (6) presents results using the Arellano-Bond (A-B) estimator, which properly includes the lagged test score as well as accounts for the panel dimension of the data[12].

From columns (1)-(3) we can see that although in the cross section, low caste children have higher test scores than high caste children, this is not the case within schools. This result suggests that low caste children are attending better schools. In all specifications in Table 5, the estimated coefficient for switching to a high caste teacher is not statistically different from zero.

In Table 6, I disaggregate by caste type of the child to identify the effect of the interaction between child and teacher caste. Columns (1)-(3) are school fixed effects regressions, and

[12] Lagged dependent variable models with fixed effects are appropriately estimated with the A-B estimator, as simply including the lag within a fixed effects model induces correlation between the error term and the lag (Cameron and Trivedi, 2009).

columns (4)-(6) are child fixed effects regressions. Columns (3) and (6) also include the lagged test score. The school fixed effects regressions show no effect of the caste interaction dummies on test score outcomes, but the child fixed effects regressions show a positive effect of high caste teachers for low caste children. However, the coefficient is not significant in specification (6), which includes the lagged test score. Including the lagged test score would be preferable, but it removes much of the variation in child-teacher caste combinations. In the regressions that include the lagged test score, the first year of data is lost so instead of three changes, there are only two. Although there are four years of data on children, very little teacher data was collected in the fourth year as most children were in middle school by then, and middle school teachers were not surveyed. As a result, there are only 100 observations for this year, so losing the first year removes many of the switches in the data. With 2,642 child*year observations over all four years, there are only 120 switches. Without the first year there are 1,492 observations and only 46 switches. This is not sufficient to precisely estimate these coefficients. Again, it is not the case that children are switching to high/low caste teachers based on their previous test scores (see Appendix Table 19). Lagged test scores do not predict switching between high and low caste teachers.

Consequently, (5) in Table 6 is the preferred specification with all child, teacher and school controls, and child fixed effects. High caste children perform equally well when taught by high or low caste teachers. However, low caste children perform significantly better when taught by high caste teachers. Switching from a low caste teacher to a high caste teacher increases the test scores of low caste children by 0.17 standard deviations on average, and this effect is significant at the five per cent level. That the coefficient from the school fixed effects regression differs so much from that of the child fixed effects regression shows the importance of controlling for this child-level unobserved heterogeneity. The results suggest that it is 'worse' low caste children that are switching to high caste teachers. The interaction between child and teacher caste matters for learning outcomes in Pakistan. These results are consistent with the findings in (Hanna and Linden, 2012), where the authors find that low caste teachers graded low caste children more harshly. We will return to the potential mechanism of discrimination in the next section.

As a robustness check, I re-run specification (3) in Table 6 in two ways. I restrict the sample first to schools for which the observed frequencies of all four possible caste matches fell within the 95% confidence interval for the caste match groups, which was constructed using the simulated data. I then restrict the sample to village-years that passed the Chi-squared distribution test[13]. Appendix Table 21 contains the results with the dummies for the interaction between child and teacher caste. When the sample is restricted in these ways, the results are stronger. High caste teachers once again do not matter for high caste children, and low caste children perform significantly better when taught by high caste teachers. For low caste children, switching to a high caste teacher increases test scores by 0.27 standard deviations (significant at the 10% level) when the sample is restricted to schools that pass the confidence interval test, and increases test scores by 0.22 standard deviations (significant at the 5% level) when the sample is restricted to village-years that pass the Chi-squared distribution test.

I also consider whether it matters if the child and teacher are of the same caste group. I construct a dummy variable equal to one if the child and teacher share the same caste (*biraderi*, endogamous kinship group) and include that instead of the dummies for child and teacher caste type in equation (3). I try this for all children, and then separately for high and low caste children (see Table 22 in the Appendix). Overall, the effect of belonging to the same caste group as one's teacher has zero effect. This is also the case for high caste children. However, for low caste children, test scores are 0.22 standard deviations lower when they belong to the same caste group as their teacher. This is very similar to the difference for low caste children taught by high and low caste teachers.

Table 7 investigates the heterogeneity of this effect further, and shows how the results differ by gender of the child and for the type of school the child attends (public or private). Again, for each type of child in terms of caste and gender, the omitted category is being matched with a low caste teacher. Column (1) includes only child fixed effects and no controls, column (2) adds time dummies, column (3) adds child controls, column (4) adds teacher controls, and column (5) adds school controls, to make the full set of controls. Column (6) contains results for children in public schools, and column (7) for children in private schools. The results are relatively stable over specifications. The effect of a low caste child performing better when matched with a high

[13]No schools failed the Chi-squared distribution test. For village-years that pass the 95% confidence interval test, there are no switches between high and low caste teachers within children remaining once the sample is restricted and so the coefficients cannot be estimated.

caste teacher appears to be stronger for boys than for girls[14]. For low caste boys, switching from a low caste to a high caste teacher increases test scores by 0.29 standard deviations, and this is significant at the one per cent level. This effect is not significant in private schools, but is significant in public schools. However, the p-value in a test for the equality of the coefficient on 'child low caste male, teacher high caste' between the public and private school specifications is 0.779, so they are not significantly different.

I also look at what channel the higher test scores for children taught by high caste teachers is coming through; how are these higher test scores are achieved? It could be that parents invest more in their children's education. Parents can do this by increasing educational expenditures, by helping the child with their schoolwork, or by making it a point to get to know the child's teacher by meeting with them regarding their child's performance. It could also be that children work harder, and this could be of their own accord or with encouragement from parents.

The school survey asked teachers whether they had met the child's parents in the last month, and if so, whether the meeting had been to discuss the child's performance in school. The household survey asked parents about monthly education expenditures for each child, and how many hours per week were spent helping the child with their homework. The household survey also collected extensive data on child time use, including the number of minutes per day spent on housework and paid work, homework, leisure (including sleep/rest, play, and media), and learning (time at school and on private tutoring). Table 8 displays regressions of the household investment and child time use variables on the same specification as (3) with the full set of child, teacher and school controls, as well as time dummies and child fixed effects. Column (2) shows that low caste boys in public schools spent significantly more time per day on homework when taught by high caste teachers, on average 29 minutes more per day. 28 additional minutes per day is a substantial amount; if the child does homework every week day, this amounts to almost two and a half hours extra per week. The mean number of minutes per day spent on homework is 143 minutes for low caste boys in the sample, so an additional 28 minutes is a 20% increase. None of the other outcomes show significant effects for low caste boys. It appears that what is happening is not that low caste households are investing more, but that children are working harder.

[14]The coefficient for low caste girls in public schools is identified off only 8 switches. I will not focus on this result since so few children are driving it.

5.2 Mechanisms

In the cross section, low caste children have higher test scores than high caste children. Within schools, there are no differences, but low caste children are selecting better schools. Children on average do not have differential learning outcomes when taught by high versus low caste teachers. It is low caste boys in particular that appear to benefit from being taught by high caste teachers, and they work harder when taught by them. There are several possible reasons for these findings, and I explore seven of them here. It is possible that the finding of no difference in learning outcomes between high and low caste children within schools masks heterogeneity depending on whether the school is high or low caste dominant. If a school is high caste dominant, low caste children could feel like outsiders. Perhaps low caste children have high returns to education. Teacher caste may still matter, but high caste teachers may differ from low caste teachers in terms of unobservable characteristics that affect only low caste children. The result on high caste teachers and low caste boys could be because these high caste teachers serve as role models to low caste boys. Alternatively, perhaps low caste teachers discriminate against low caste boys, or high caste teachers favour low caste boys. It could be the case that psychological factors of low caste boys are affecting their behaviour; they may try harder in order to prove themselves. A final possibile mechanism is that high caste teachers can provide access to certain benefits for low caste boys through their patronage networks if they perform well in school.

High versus low caste dominant schools

I begin with looking further into the effects of child caste. It is easy to imagine that low caste children may be treated differently if they are surrounded by predominantly high caste peers. The average school has five different caste groups in the student population. However, most schools (81%) are high caste dominant. Table 9 displays results from a school fixed effects regression of average test scores on dummies for the interaction between child caste and whether a school is high caste dominant. A school is considered high caste dominant if the proportion of children enrolled in grades 1 to 5 who are high caste is greater than the proportion of children enrolled in grades 1 to 5 who are low caste. Since a school is either high or low caste dominant, the coefficients reflect the difference in test scores between high and low caste children in high or low caste dominant schools. Table 9 shows that there are no differences between high and low caste children in either high or low caste dominant schools.

Returns to Education

Next, I test whether low caste children have high returns to education. If they do, this can help explain why we see that low caste children have higher test scores than high caste children in the cross section, and why they select better schools. I look at the parents of the children in the sample and compare returns to education for high caste and low caste men in the same village. Only 105 women report earning a positive wage. In addition, it is boys whose behaviour is most affected. As a result, I estimate the earnings functions only of fathers. Table 10 provides the results from regressing the log of the monthly wage separately for high and low caste men on dummy variables for having completed primary school, middle school, high school, or more education than high school. The omitted category is having completed either no education or not having finished primary school. I include as many individual and household level controls as possible (age, marital status, household size, deaths in the household, whether the household owns land, whether anyone left the household, whether the household receives remittances, total expenditures, and the asset index). Returns to completing primary school are identical (and indistinguishable from zero) for both high and low caste men. Returns to completing middle school, high school, and more than high school appear higher for low caste men than for high caste men (see also Figure 5). However, the coefficients for high and low caste men are not individually or jointly significantly different from one another. What this does show is the importance of education for economic (and possibly social) mobility for the low caste male children in the sample. Returns to education are high for low caste boys.

Teacher Quality

The argument could also be made that high caste teachers are simply high quality teachers. The higher performance of low caste boys paired with high caste teachers might be driven by a specific type of teacher quality. To investigate this further, I run a regression of children's average test scores on child, teacher and school controls, but this time including teacher*time fixed effects. I also include a dummy variable for high caste students. The coefficient on this dummy shows the differences in test scores for high and low caste boys taught by the same teacher in the same year (children in the same class). This differences out time-invariant unobserved aspects of teacher quality. Table 11 provides the results. High caste boys have significantly lower test scores than low caste boys in the same class. This is true for both high and low caste teachers. Another indication that high caste teachers are not simply higher quality teachers is that they do not similarly benefit high caste children. High caste children perform equally when taught by high and low caste teachers, as the results of Table 7 show. Table 7 also shows that including teacher observables in the regression does not change the coefficient on the caste dummy variables very much at all (comparing columns (3) and (4)). This indicates that teacher observable characteristics that could be related to quality also do not vary systematically by caste. So it is not the case that high caste teachers are just better teachers; it is that some children perform significantly better when taught by them. These results are not consistent with the notion that teacher quality affects all students approximately equally.

Discrimination

Now I will focus on the interaction between child and teacher caste to try to understand why low caste boys benefit from being taught by high caste teachers. I cannot test whether teachers are biased when they are grading children. However, the way in which teachers perceive and judge the performance of children could potentially be important for learning outcomes. To test this, I construct a measure that can be thought of as measuring biased perceptions. Teachers were asked to rate children on their academic performance on a scale of 1 to 10. I rank children in the same class according to these ratings. I also rank children in the same class according to an average of their three test scores. I then subtract the teacher's ranking from the test ranking, and create a dummy variable for whether this difference is negative (meaning that the teacher overrates the child's performance). This outcome is regressed on the same four caste combination dummies and controls as in Table 7, along with child fixed effects and time dummies. The results are contained in column (1) of Table 12. The coefficient on the dummy for low caste boys taught by high caste teachers is not significantly different from zero. It does not look as if high caste teachers are over- or under-rating the academic performance of low caste boys. Interestingly, high caste teachers appear to be overrating high caste boys. This does not seem to affect their test scores, however.

Teachers may actually be able to rate children's performance quite accurately if they have more information on the child's ability than one year of test scores can provide (for example, they may be aware of previous performance or family circumstances). The test score measure is noisy, so if teachers do have more knowledge on a child's true ability, then the outcome variable above may not reflect discrimination; it would reflect the deviation from true ability. A teacher's assessment of a child's ability may be a function of true ability of the child and some degree of error. Knowledge about children's true ability may differ by caste of the child and teacher. If this is the case, the coefficients on the caste interaction dummies in Table 12 will be biased, as there will be systematic measurement error in the outcome variable that is correlated with caste. If teachers of the same caste-type as a child have better information (so deviation of the ranking from true ability is lower) than teachers of the opposite caste-type as a child, then the coefficient for low caste children taught by high caste teachers will be biased downwards (upwards) if true ability is higher (lower) than ability demonstrated by the test score. As a check, I construct a test score measure that is the average of not just the three current test scores, but also all test scores that occurred in previous years for which I have data[15]. I then rank the students in the same class again according to this new test measure and compare the difference between the ranking of the teachers rating and the ranking of this cumulative test score. If teachers are using information on past test scores in their assessment, then including this information in the discrimination measure should reduce the measurement error in their ranking (possibly by less for low caste children, however). The results are contained in column (2) of Table 12. The results are actually quite similar to those of column (1), so I do not believe that this type of systematic measurement error is a problem here.

Role model effects

Next, I focus on role model effects. One interpretation of role model effects that was discussed in Section 3 was that teachers who are more similar to the child could elicit better performance. However, this does not seem to be the case, as it is high caste teachers that produce high test score outcomes for low caste boys. Rather, opposite caste-type teachers may be serving as role models. Another way to look at role model effects is that a child may like to emulate his/her

[15]In the first year, only the three current-year tests are used.

teacher. To check whether high caste teachers could be serving as role models to low caste children, I use data on what the children report wanting to do when they grow up. In the third and fourth rounds of the survey, the children were asked to state what profession they would like to eventually go into, and I construct a dummy variable for whether the child would like to be a teacher (27% of the sample overall), which could be a sign that the child would like to emulate their teacher, and so may consider the teacher as a role model. I also construct a dummy variable for whether the child reports wanting to have a skilled job apart from teaching (doctors, government jobs, politicians, engineers, or private sector jobs). Perhaps high caste teachers could inspire children to have high aspirations. I regress these outcomes on child and teacher caste-type and gender dummies within schools[16]. The omitted category is a low caste male child matched with a low caste teacher. The results are reported in Table 13. It appears that low caste boys report wanting to become teachers significantly less when they are taught by high caste teachers than low caste teachers. Interestingly, high caste boys appear not to want to go into teaching, regardless of whether they are taught by high or low caste teachers (the p-value for the difference in coefficients for high caste boys taught by high and low caste teachers is 0.625). Low caste boys taught by high caste teachers are marginally more likely to report wanting to have a high skilled job than low caste boys taught by low caste teachers. Again, high caste boys are very likely to report wanting a high skilled job, regardless of the caste of their teacher. It does not appear as if low caste boys would like to emulate their teachers by also becoming teachers. Instead, they would like to go into other high skilled professions, many of which pay better than teaching (for example, doctors and engineers). This result points to the next mechanism.

Psychological Aspects and/or Patronage

Finally, I explore two other mechanisms, which are difficult to isolate from one another with these data. These are: psychological aspects of caste, and the role of patronage in the education sector. I examine the possibility that low caste boys are working harder in order to prove themselves to high caste teachers to dispel the stigma associated with low caste groups, and the possibility that high caste teachers are able to help low caste boys with educational

[16] There are not enough observations to include child fixed effects since the question was only asked in the third and fourth rounds of the survey, and so I include school fixed effects instead.

or employment opportunities, thereby increasing their already high returns to education when taught by them. Both of these would result in similar behaviour, and unfortunately I do not have data that would allow me to distinguish between the two.

If teachers are helping students through their patronage networks, we would expect the effect of high caste teachers on low caste boys to be larger in cases in which caste is more salient. In these cases, high caste teachers are likely to have greater influence. Of course, in places where caste is more salient, low caste children may also just have more impetus to try harder. I re-run equation (3) separately for the three districts in the sample: Attock (North), Faisalabad (centre) and Rahim Yar Khan (South). Caste differences are more salient in the North of Punjab than in the South. Table 14 shows that the effect for low caste boys is much stronger in Attock than in both Faisalabad and Rahim Yar Khan. The p-value for a test of equality of all three low caste boys' coefficients across the regressions is 0.029. In addition, the coefficient for Attock is significantly different from that for Faisalabad (p-value 0.030) and from Rahim Yar Khan (p-value 0.009). There is no significant difference between the coefficients for Faisalabad and Rahim Yar Khan (p-value 0.396).

These results, as well as the previous result that low caste boys spend 20% more time on homework, are also consistent with another psychological aspect of caste: that high caste teachers may have more authority over low caste children than they do over low caste children (in general, but also to enforce homework, for example). With the data available it is difficult to tease out which of these effects dominates.

The results in this section help to shed some light on the reasons for which low caste children have higher test scores and choose better schools, high caste teachers do not matter on their own, and low caste boys benefit from being taught by high caste teachers because they have higher test scores and they work harder. The mechanism cannot be proven, but the data does point to the possibility that either low caste boys want to prove themselves and so work harder, or that high caste teachers increase the already high returns to education of low caste boys because they are able to help them later on, thereby leading these boys to work harder. All other explanations cannot be completely ruled out, but the data certainly point to psychological factors or patronage networks as possibilities.

What is Caste?

Since there are important effects of caste on learning outcomes, it is important to understand what these social differences between castes mean. It is possible that this measure of social distance is capturing something else that is related to caste. As discussed in previously, there are gaps in learning between households that are poorer, and with lower levels of education. Although there is much overlap in characteristics between high and low caste households, are these inequalities the same as caste inequalities? I focus on children and look at two alternatives: household wealth and parental education. Instead of splitting children into high and low caste, I split them into 'not poor' and 'poor', and educated and uneducated father[17]. I use the household asset index and classify households as poor if they fall into the bottom quintile of this index. The average test scores of the children are then regressed on dummies analogous to the teacher-student caste interaction dummies, but with wealth and parental education for children, and high and low caste as before for teachers. Table 15 contains the results for wealth in column (1) and for parental education in column (2). The coefficients do not resemble those of the original caste interaction dummies. There appear to be no effects of differences in wealth or parental education levels. This shows that children's caste does not map completely onto wealth, or onto household education. It is important to understand what caste means for teachers, as well. As shown previously, caste does not mean observed or unobserved quality for teachers.

In summary, social distance is important for child learning outcomes. Low caste children have high returns to education, and invest in their human capital. Although teacher caste does not affect learning outcomes on its own, the interaction between the caste type of teachers and students does matter. Low caste boys benefit from being taught by high caste teachers, and they spend significantly more time on homework. This effect does not differ depending on whether a school is high or low caste dominant. Low caste boys have high returns to education, as evidenced by high returns to schooling experienced by their fathers. I cannot find any evidence of discrimination on the part of teachers, nor for high caste teachers serving as role models to low caste boys. In addition, the effects for low caste boys are much stronger in the North of Punjab than in the South. This last result is suggestive of either low caste boys feeling the

[17]The results do not differ if mother's education is used instead.

need to prove themselves to high caste teachers, or of high caste teachers increasing the returns to education for low caste students by helping them get access to educational and employment benefits through patronage networks.

6 Conclusion

This paper has sought to understand what role caste plays in the learning outcomes of children in Punjab, Pakistan, and contributes to the literature on social distance in education. It attempts to identify the effect of child caste, teacher caste, and the interaction between child and teacher caste on learning outcomes. Many measures are employed in order to reduce bias from non-random sorting of children and teachers both to schools and within schools. Seven possible mechanisms of how caste differences between teachers and students may affect learning outcomes are then explored: social dynamics in schools, returns to education, teacher quality, discrimination, role model effects, psychological factors, and patronage networks.

I find that although in the cross-section, low caste children have higher test scores than high caste children, within schools this is not the case. However, low caste children attend better schools because they have high returns to education. In addition, differences between high and low caste children do not vary with the caste composition of the school. Teacher caste on its own does not matter for learning outcomes. It is not the case that high caste teachers are higher quality teachers; low caste children outperform their high caste peers in the same class. The interaction between teacher and child caste does matter for learning outcomes. I find that low caste male children perform significantly better when taught by high caste teachers compared to low caste teachers, and that they also spend significantly more time on homework when taught by high caste teachers. In addition, this effect is stronger in the North of Punjab where caste is more salient. The paper finds no evidence of discrimination by teachers in perceptions of child ability, or of role model effects. Finally, caste does not map perfectly either onto inequalities in wealth or in parental education levels. The results of this study suggest that caste is a characteristic of children and teachers that matters for learning in rural Punjab. The distribution of teachers and students across schools, which determines which teachers students are exposed to, can have important implications for reducing gaps in educational opportunities in low-income countries.

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Figure 1: Characteristics of High and Low Caste Households

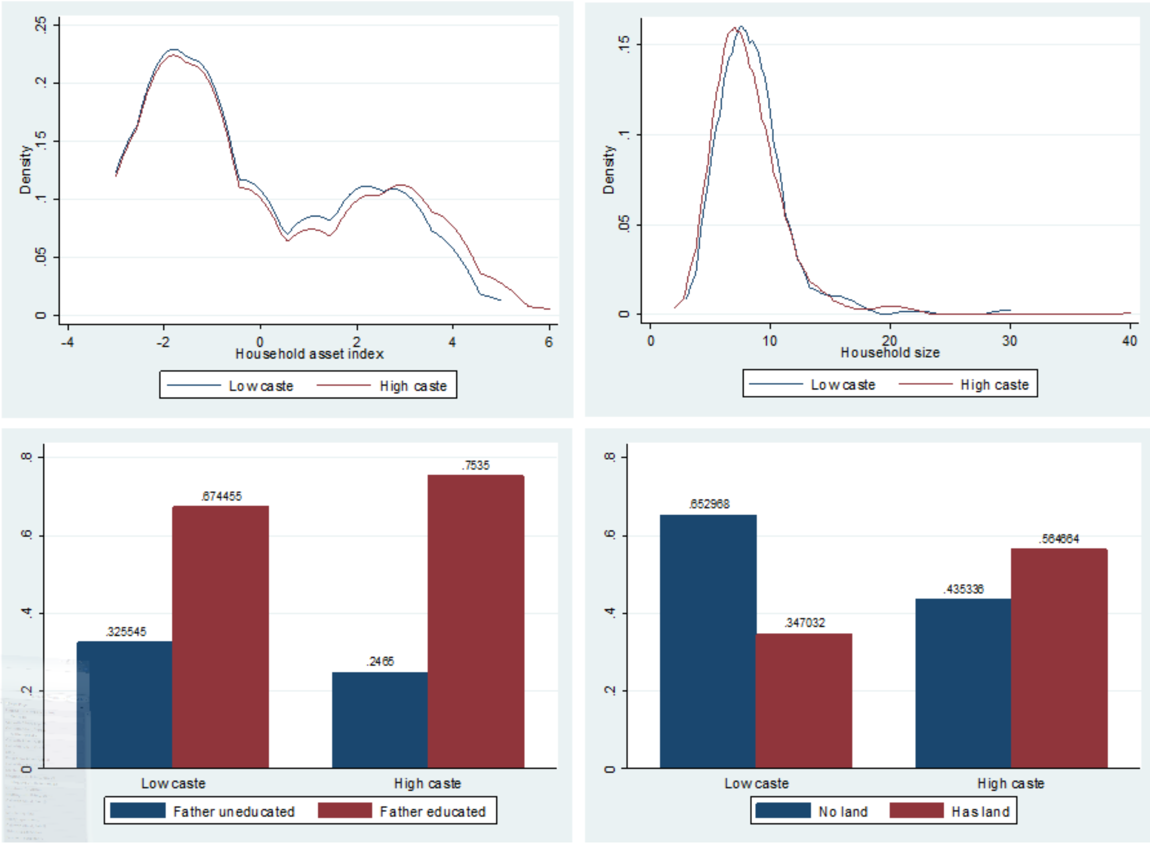

Figure 2: Children's Test Scores

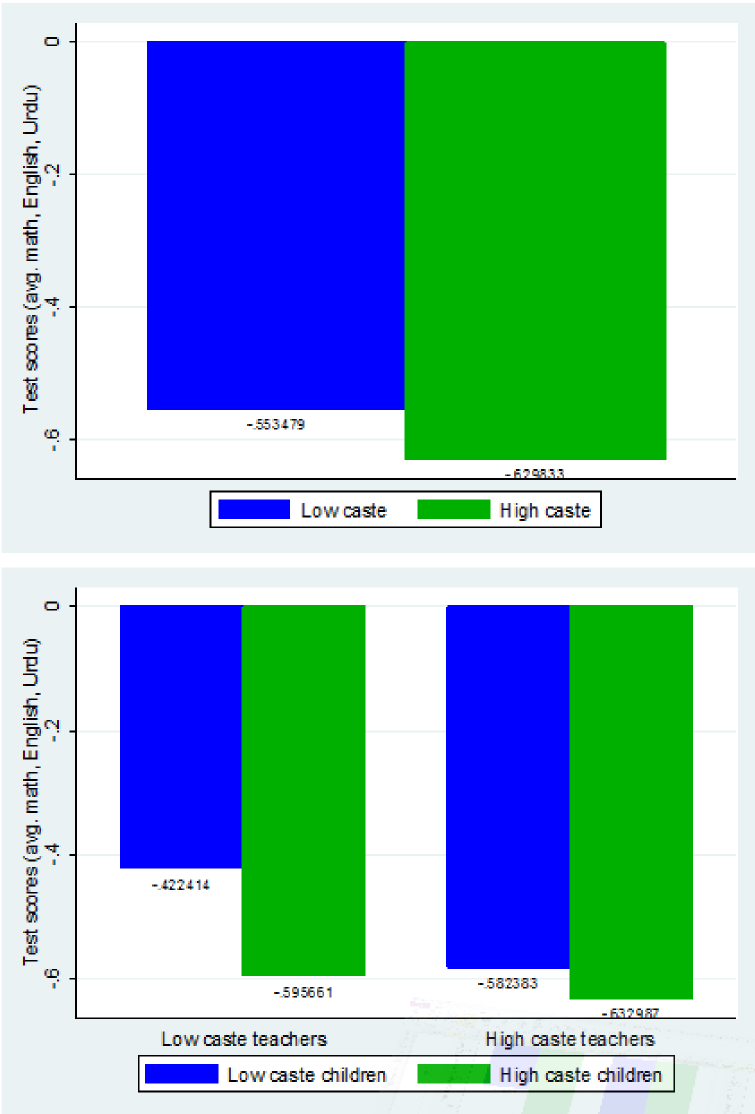

Figure 3: P-values from Chi-squared test within villages

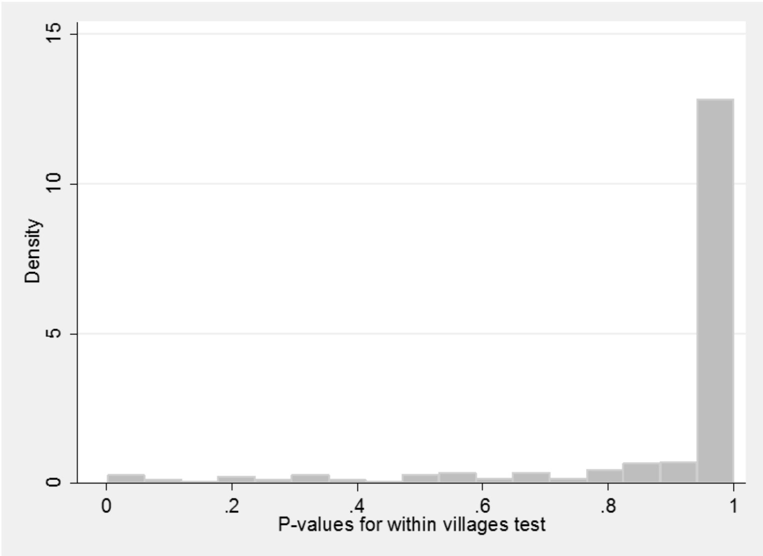

Figure 4: P-values from Chi-squared test within schools

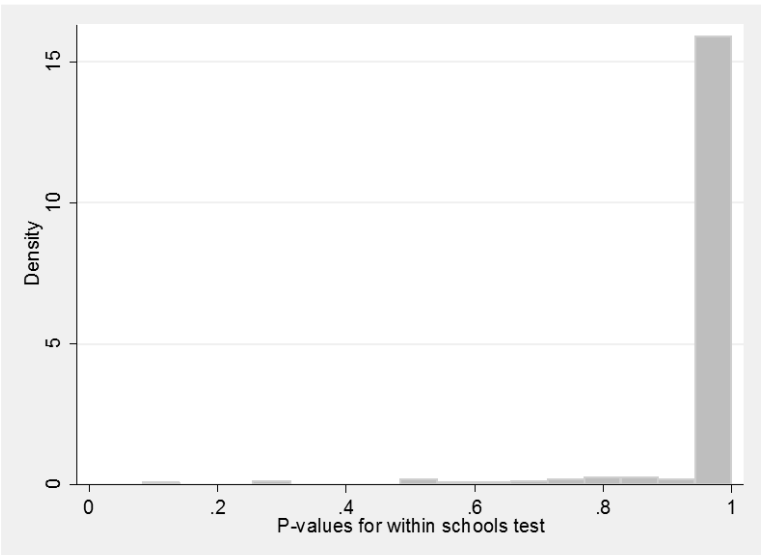

Figure 5: Returns to Education

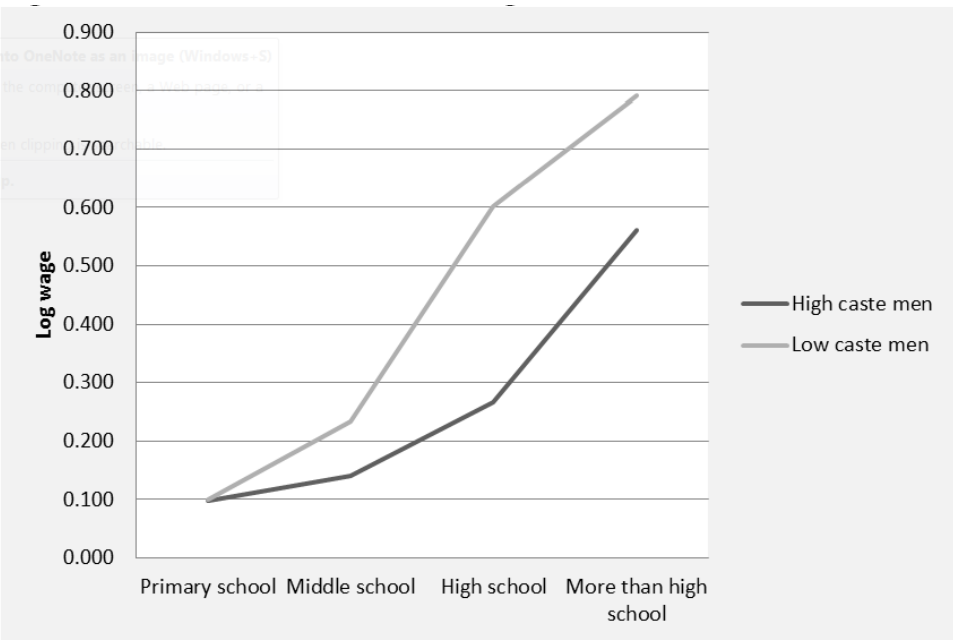

Table 1: Descriptive statistics of children

	High caste				**Low caste**			
Children	**Boys**		**Girls**		**Boys**		**Girls**	
Number of children*time	1,068		932		393		249	
Proportion of children	0.404		0.353		0.149		0.094	
Characteristics	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Average age	10.15	1.67	10.30**	1.65	10.12	1.64	10.45**	1.65
Grade	3.91	0.82	3.89	0.82	3.92	0.79	3.82	0.80
Education	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Enrolled in private school	0.25	0.44	0.29	0.45	0.21	0.41	0.21	0.41
Enrolled in school (2011)	0.49	0.50	0.45	0.50	0.41	0.49	0.26**	0.44
Highest grade (2011)	7.89	1.97	8.15*	2.06	7.84	2.21	7.84	2.26
Households	Mean		Sd		Mean		Sd	
Household size	8.10		3.42		8.38*		2.96	
Owns land	0.56		0.50		0.35***		0.48	
Monthly educ. expend.	235		160		215***		147	
Asset index	-0.09		2.29		-0.25		2.21	
Mother uneducated	0.61		0.49		0.74***		0.44	
Father uneducated	0.37		0.48		0.51***		0.50	

Asterisks denote significant differences between boys and girls, and between high and low caste households.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Descriptive statistics of teachers

	High caste		Low caste		All teachers	
Number of teachers*time	2,357		285		2,642	
Proportion of teachers	0.892		0.108		1.00	
	Mean	Sd	Mean	Sd	Mean	Sd
Age	34.59	9.49	35.49	7.73	34.68	9.32
Proportion female	0.55	0.5	0.37	0.48	0.53	0.5
Originally from same village	0.39	0.49	0.35	0.48	0.38	0.49
Proportion married	0.67	0.47	0.73	0.45	0.68	0.47
Teaching experience	6.69	18.18	3.96	10.9	6.4	17.56
Education: matric	0.4	0.49	0.24	0.43	0.38	0.49
Education: FA	0.28	0.45	0.26	0.44	0.28	0.45
Education: BA	0.25	0.43	0.45	0.5	0.27	0.44
Education: MA	0.07	0.25	0.06	0.23	0.07	0.25
Any training	0.8	0.4	0.88	0.32	0.81	0.4
Teaching in a private school	0.26	0.44	0.24	0.43	0.25	0.44
Math test	2.88	1.01	2.83	1.01	2.88	1.01
English test	2.38	0.93	2.59	0.85	2.4	0.92
Urdu test	2.68	0.85	2.65	0.76	2.67	0.84
Minutes/week grading	32.03	36.17	34.72	34.87	32.33	36.03
Minutes/week preparation	32.27	40.45	30.08	37.14	32.03	40.09
Minutes/week private tutoring	12.38	45.03	12.37	52.52	12.38	45.93
Proportion mother uneducated	0.3	0.46	0.32	0.47	0.3	0.46
Proportion father uneducated	0.69	0.46	0.65	0.48	0.69	0.46
Absences last month	1.98	2.56	2.08	3.12	1.99	2.63

Table 3: Matches and switches between teachers and students

Panel A: Matches			Teacher			
			High caste		Low caste	
			Male	Female	Male	Female
Child	High caste	Male	765	216	79	8
		Female	27	823	21	61
	Low caste	Male	254	59	76	4
		Female	11	202	3	33
Panel B: # switches			To Teacher			
			High caste		Low caste	
			Male	Female	Male	Female
From Teacher	High caste	Male	525	11	23	0
		Female	35	672	6	17
	Low caste	Male	47	5	54	0
		Female	5	17	0	40
Panel C: Proportion of switches			To Teacher			
			High caste		Low caste	
			Male	Female	Male	Female
From Teacher	High caste	Male	0.36	0.008	0.016	0
		Female	0.024	0.461	0.004	0.012
	Low caste	Male	0.032	0.003	0.037	0
		Female	0.003	0.012	0	0.027

Table 4: Proportion of villages and schools that fall within the 95% confidence interval

Category	**Proportion**
Village Level	
Teacher high caste, Child high caste	72.93%
Teacher high caste, Child low caste	78.66%
Teacher low caste, Child high caste	73.25%
Teacher low caste, Child low caste	87.58%
School Level	
Teacher high caste, Child high caste	86.47%
Teacher high caste, Child low caste	92.48%
Teacher low caste, Child high caste	86.84%
Teacher low caste, Child low caste	96.62%

Table 5: Child caste and teacher caste

Outcome: average of math, English and Urdu test scores						
	(1)	(2)	(3)	(4)	(5)	(6)
		School FE			Child FE	
	Basic	Controls	+ lag	Basic	Controls	+ lag
High caste teacher	0.048	0.018	0.074	0.030	0.016	-0.085
	(0.122)	(0.095)	(0.124)	(0.069)	(0.070)	(0.140)
Child high caste	0.025	-0.016	-0.072			
	(0.078)	(0.074)	(0.057)			
Lagged test scores			0.502***			0.298*
			(0.057)			(0.152)
Observations	2642	2642	1492	2642	2642	1492
R^2	0.115	0.234		0.409	0.422	

Standard errors in parentheses.

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

All regressions include child, teacher and school controls, and time dummies.

Standard errors clustered at the level of the fixed effect.

Table 6: Interaction between child and teacher caste

Outcome: average of math, English and Urdu test scores						
	(1)	(2)	(3)	(4)	(5)	(6)
		School FE			Child FE	
	Basic	Controls	+ lag	Basic	Controls	+ lag
Child high caste,	0.086	-0.001	-0.044	-0.044	-0.059	-0.249
teacher high caste	(0.194)	(0.162)	(0.165)	(0.094)	(0.096)	(0.168)
Child low caste,	0.064	0.015	0.018	0.181**	0.168**	0.232
teacher high caste	(0.185)	(0.148)	(0.168)	(0.085)	(0.081)	(0.181)
Child high caste,	0.046	-0.020	-0.149			
teacher low caste	(0.219)	(0.204)	(0.210)			
Lagged test scores			0.501***			0.299**
			(0.057)			(0.152)
Observations	2642	2642	1492	2642	2642	1492
R^2	0.115	0.234		0.410	0.423	

Standard errors in parentheses.

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

All regressions include child, teacher and school controls, and time dummies.

Standard errors clustered at the level of the fixed effect.

Table 7: Child and teacher caste interaction by gender and public/private school

	Outcome: average of math, English and Urdu test scores						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Basic	+ Time	+ Child	+ Teacher	+ School	Public	Private
C: high, female. T: high	-0.147	0.014	0.010	-0.012	-0.001	0.131	-0.060
	(0.157)	(0.098)	(0.099)	(0.098)	(0.098)	(0.169)	(0.154)
C: high, male. T: high	0.061	-0.088	-0.095	-0.113	-0.105	-0.206	-0.057
	(0.185)	(0.148)	(0.151)	(0.151)	(0.152)	(0.219)	(0.142)
C: low, female. T: high	-0.121	-0.126	-0.124	-0.174	-0.175	-0.401**	-0.141
	(0.248)	(0.132)	(0.132)	(0.130)	(0.130)	(0.192)	(0.187)
C: low, male. T: high	0.563***	0.291***	0.294***	0.288***	0.290***	0.235**	0.177
	(0.110)	(0.097)	(0.096)	(0.091)	(0.089)	(0.108)	(0.181)
Observations	2642	2642	2642	2642	2642	1970	672
R^2	0.009	0.411	0.416	0.423	0.424	0.416	0.485

Standard errors in parentheses.

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

All regressions include child fixed effects and standard errors clustered at the child level.

C denotes child, T denotes teacher.

Table 8: Teacher-student caste, child time use and household investments

Outcome	(1) House/paid work	(2) Homework	(3) Leisure	(4) Learning	(5) Parents met teacher	(6) Met re: performance	(7) Hrs helping w/ hwork	(8) Education Expenditure
C: high, female. T: high	-13.806	-11.609	49.928	2.884	-0.225*	0.064	1.005	17.293
	(28.200)	(15.285)	(47.035)	(25.801)	(0.132)	(0.139)	(4.021)	(35.544)
C: high, male. T: high	5.503	16.359	-32.548	-36.401	-0.305***	-0.385***	-2.143	-10.604
	(9.606)	(16.817)	(49.675)	(28.233)	(0.117)	(0.110)	(1.844)	(29.458)
C: low, female. T: high	-57.321**	-27.763	33.712	47.137	-0.125	-0.424	0.582	-19.694
	(27.373)	(32.629)	(57.704)	(29.741)	(0.484)	(0.315)	(2.223)	(57.237)
C: low, male. T: high	**-14.421**	**28.358****	**-7.809**	**3.236**	**0.163**	**0.142**	**0.473**	**-17.408**
	(11.061)	**(14.418)**	**(50.858)**	**(22.548)**	**(0.169)**	**(0.178)**	**(1.757)**	**(27.714)**
Observations	2144	2093	2144	2144	1202	1202	658	2117
R^2	0.051	0.041	0.078	0.029	0.072	0.048	0.140	0.196

Standard errors in parentheses.

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

All regressions include child, teacher and school controls, time dummies, and child fixed effects.

Standard errors clustered at the child level.

Table 9: High and low caste dominant schools

Outcome: average of math, English and Urdu test scores	
	(1)
High caste child, high caste dominant school	-0.113
	(0.069)
Low caste child, high caste dominant school	0.041
	(0.081)
Observations	2642
R^2	0.423

Standard errors in parentheses.

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

Regression includes child, teacher and school controls, and time dummies.

Standard errors clustered at the level of the fixed effect (school).

Table 10: Returns to Education

Outcome: log of the monthly wage				
	(1)		(2)	
	High caste men		Low caste men	
	coef	se	coef	se
Primary school	0.099	0.072	0.099	0.136
Middle school	0.141*	0.084	0.234	0.195
High school	0.266**	0.115	0.602**	0.302
More than high school	0.562***	0.151	0.791**	0.353
Constant	7.627***	0.291	7.448***	0.47
Number of observations	1,020		314	
R^2	0.27		0.34	

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

Omitted category: less than primary school.

Regressions include individual and household controls, as well as time dummies and village fixed effects.

Standard errors clustered at the village level.

Table 11: Test scores with teacher fixed effects

	Outcome: average of math, English and Urdu test scores			
	(1)	(2)	(3)	(4)
	All Children	Boys	Boys (low caste teachers)	Boys (High caste teachers)
Child high caste	-0.026	-0.144*	-0.285	-0.113
	(0.054)	(0.081)	(0.345)	(0.081)
Observations	2642	1461	167	1294
R^2	0.068	0.062	0.072	0.069

Standard errors in parentheses.

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

All regressions include child, teacher and school controls, time dummies, and teacher*time fixed effects.

Standard errors clustered at the teacher*time level.

Table 12: Discrimination Effects

Outcome: difference between actual test score rank and teacher's rank of child		
	(1)	(2)
	One year	Cumulative
C: high, female. T: high	-0.263	-0.049
	(0.161)	(0.219)
C: high, male. T: high	0.256**	0.247**
	(0.125)	(0.108)
C: low, female. T: high	0.419	0.336
	(0.448)	(0.247)
C: low, male. T: high	-0.197	-0.116
	(0.197)	(0.182)
Observations	1149	1149
R^2	0.046	0.032

Standard errors in parentheses.

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

All regressions include child, teacher and school controls, and time dummies.

Standard errors clustered at the level of the fixed effect (child).

Table 13: Role Model Effects

	(1)	(2)
Outcome	Teaching Career	Skilled Job
C: high, female. T: high	-0.047	0.199
	(0.264)	(0.256)
C: high, female. T: low	0.031	0.075
	(0.295)	(0.287)
C: high, male. T: high	-0.526**	0.370
	(0.251)	(0.238)
C: high, male. T: low	-0.438**	0.538***
	(0.180)	(0.178)
C: low, female. T: high	-0.237	0.234
	(0.270)	(0.264)
C: low, female. T: low	-0.182	0.099
	(0.373)	(0.366)
C: low, male. T: high	-0.557**	0.399*
	(0.250)	(0.235)
Observations	743	743
R^2	0.136	0.086

Standard errors in parentheses.

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

All regressions include child, teacher and school controls, and time dummies.

Standard errors clustered at the level of the fixed effect (school).

Skilled jobs include: doctors, government jobs, politicians, engineers, or private sector jobs.

Table 14: Results by District

	(1)	(2)	(3)
	Attock	Faisalabad	Rahim Yar Khan
C: high, female. T: high	0.122	0.093	-0.193
	(0.150)	(0.146)	(0.183)
C: high, male. T: high	-0.097	-0.187	-0.172
	(0.271)	(0.197)	(0.159)
C: low, female. T: high	-0.125	-0.413***	0.010
	(0.158)	(0.147)	(0.132)
C: low, male. T: high	0.714***	0.278***	0.132
	(0.174)	(0.101)	(0.140)
Observations	934	981	727
R^2	0.894	0.871	0.841

Standard errors in parentheses

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

Outcome is average of math, English and Urdu test scores.

All regressions include child, teacher and school controls, and time dummies.

Standard errors clustered at the level of the fixed effect (child).

Table 15: Wealth and parental education

Outcome: average of math, English and Urdu test scores			
(1)		(2)	
Wealth	coef/se	Education	coef/se
Child: not poor, female.	-0.090	Child: educated father, female.	-0.033
Teacher: high caste.	(0.084)	Teacher: high caste.	(0.079)
Child: not poor, male.	0.026	Child: educated father, male.	0.083
Teacher: high caste.	(0.104)	Teacher: high caste.	(0.103)
Child: poor, female.	0.021	Child: uneducated father, female.	-0.107
Teacher: high caste.	(0.086)	Teacher: high caste.	(0.121)
Child: poor, male.	0.079	Child: uneducated father, male.	-0.029
Teacher: high caste.	(0.102)	Teacher: high caste.	(0.111)
Number of observations	2,642	Number of observations	2,642
R^2	0.422	R^2	0.422

Standard errors in parentheses.

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

Regressions include child, teacher and school controls, time dummies, child fixed effects.

Standard errors clustered at the child level.

A Appendix: Additional Tables

Table 16: List of high and low caste groups

Caste Name	High/Low
Aarain	High
Abbasi	High
Ansari	Low
Awaan	High
Baloch	High
Butt	High
Chachar	High
Gujjar	High
Jat	High
Laar	High
Mohana	Low
Mughal	High
Muslim Sheikh	Low
Naich	High
Pathan	High
Qureshi	High
Rajput	High
Rehmani	Low
Samija	High
Sheikh	Low
Solangi	Low
Syed	High

Table 17: Observed and Simulated Data

Within Villages					
Observed	Mean	Std. Dev.	Min	Max	Observations
Teacher high caste, child high caste.	5.299	2.999	0	14	314
Teacher high caste, child low caste.	1.511	1.511	0	8	314
Teacher low caste, child high caste.	0.511	1.024	0	5	314
Teacher low caste, child low caste.	0.354	1.256	0	11	314
Simulated	Mean	Std. Dev.	Min	Max	Observations
Teacher high caste, child high caste.	5.253	2.948	0	14	314
Teacher high caste, child low caste.	1.537	1.487	0	8	314
Teacher low caste, child high caste.	0.546	0.973	0	4.352	314
Teacher low caste, child low caste.	0.323	1.116	0	11	314
Within Schools					
Observed	Mean	Std. Dev.	Min	Max	Observations
Teacher high caste, child high caste.	5.034	4.151	0	21	266
Teacher high caste, child low caste.	1.368	2.101	0	9	266
Teacher low caste, child high caste.	0.485	1.377	0	9	266
Teacher low caste, child low caste.	0.331	1.35	0	12	266
Simulated	Mean	Std. Dev.	Min	Max	Observations
Teacher high caste, child high caste.	5.008	4.165	0	21	266
Teacher high caste, child low caste.	1.351	2.072	0	9.347	266
Teacher low caste, child high caste.	0.435	1.153	0	7.526	266
Teacher low caste, child low caste.	0.301	1.194	0	12	266

Table 18: Teachers matching to schools

	(1)		(2)	
Outcome: High caste teacher				
	OLS		Probit	
	coef	se	coef	se
Private school	-0.097	0.059	-0.819	0.789
Facilities index	-0.474	0.34	-5.736	4.246
Medium of teaching - Punjabi	-0.018	0.054	0.575	0.775
Medium of teaching - Pashto	-0.101	0.092	-0.459	0.985
Medium of teaching - Sindhi	-0.037	0.059	0.228	0.736
Medium of teaching - Seriaki	-0.049	0.103	-0.209	1.049
Medium of teaching - Other	-0.135	0.12	-0.556	1.245
Number of male teachers	0.002	0.007	0.089	0.074
Number of female teachers	-0.003	0.008	0.054	0.07
Building - Rented	0.038	0.072	0.867	0.64
Building - Government	-0.186***	0.066	-1.962***	0.677
Building - Donated	-0.06	0.056	(dropped)	
Building - Other	-0.219*	0.119	0.929	1.265
Number of students	0.000	0.000	-0.001	0.002
Number of govt. schools within 5 mins	-0.037*	0.021	-0.476**	0.202
Number of Islamic schools within 5 mins	-0.018	0.027	-0.065	0.21
Number of private schools within 5 mins	0.004	0.026	0.018	0.229
Number of govt. schools within 5-15 mins	0.004	0.013	-0.152	0.212
Number of Islamic schools within 5-15 mins	-0.011	0.013	-0.519***	0.173
Number of private schools within 5-15 mins	0.002	0.002	0.258	0.187
Number of govt. schools greater than 15 mins	-0.002	0.001	-0.104	0.072
Number of Islamic schools greater than 15 mins	0.001	0.001	0.094	0.075
Number of private schools greater than 15 mins	0.001	0.001	0.000	0.018
Time from school to nearest phone	0.059	0.036	0.695*	0.378
Time from school to nearest bank	-0.012	0.025	-0.152	0.291
Time from school to nearest health facility	-0.015	0.019	-0.315	0.241
Time from school to nearest transport facility	-0.024	0.023	-0.374	0.289
Time from school to nearest government office	-0.001	0.001	-0.083	0.203
School has a library	-0.339	0.236	-4.268	2.948
School has a computer	-0.500*	0.297	-5.748	3.698
School has a place for sports	-0.4	0.291	-5.069	3.586
School has a hall	-0.316	0.226	-4.522	2.835
School has walls surrounding it	-0.338	0.243	-4.191	2.936
School has fans	-0.574	0.4	-6.941	5.123
School has electricity	-0.605	0.42	-7.66	5.311
Toilets - latrine	-0.081	0.086	-1.528	0.975
Toilets - flush	-0.145	0.12	-2.031	1.541
Toilets - septic tank	-0.354	0.222	-3.781	2.408
Toilets - other	-0.354	0.233	-4.562	3.087

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Table 18 – *Continued from previous page*

Outcome: High caste teacher				
	(1)		(2)	
	OLS		Probit	
	coef	se	coef	se
Water - outside school	-0.1	0.119	-1.381	1.243
Water - tap/well inside school	-0.169	0.175	-2.028	2.129
Water - pump inside school	-0.314	0.249	-3.816	3.002
Water - official water supply	-0.472	0.34	-5.014	3.986
Sitting arrangement - mats	-0.066	0.085	-0.904	1.197
Sitting arrangement - desks and chairs	-0.178	0.153	-1.968	1.911
Sitting arrangement - desks/chairs/mats	-0.225	0.202	-2.437	2.635
Sitting arrangement - other	-0.255	0.268	(dropped)	
School is high caste dominant	0.104*	0.057	1.055**	0.47
Contracts for teachers	-0.04	0.05	-0.599	0.585
School awards teachers bonuses	0.091**	0.038	0.846**	0.426
School has an SMC	0.051	0.048	0.915	0.557
Constant	3.146**	1.552	28.585	19.284
Number of observations	1,662		627	
R^2	0.115		0.455	

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

Regressions include time dummies and village fixed effects.

Standard errors clustered at the village level.

1.0

Table 19: Lagged test scores and switching between high and low caste teachers

	All children			High caste male			High caste female			Low caste male			Low caste female		
	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Lagged average test scores	-0.011	-0.015	-0.019	-0.003	-0.021	-0.038	-0.028**	0.002	-0.003	0.003	-0.033	-0.044	-0.015	0.014	-0.039
	(0.009)	(0.011)	(0.036)	(0.013)	(0.020)	(0.066)	(0.014)	(0.019)	(0.053)	(0.030)	(0.038)	(0.103)	(0.034)	(0.025)	(0.067)
Age	-0.006	-0.003	-0.009	-0.005	-0.012	-0.038	-0.005	0.013	0.024	-0.002	-0.015	-0.068	-0.034*	-0.018	-0.006
	(0.005)	(0.006)	(0.023)	(0.008)	(0.011)	(0.041)	(0.007)	(0.011)	(0.037)	(0.013)	(0.020)	(0.056)	(0.018)	(0.018)	(0.083)
Female	0.093***	0.029	1.033***												
	(0.025)	(0.024)	(0.081)												
Child high caste	-0.053***	-0.010	-1.078***												
	(0.019)	(0.015)	(0.081)												
Grade 3	0.067	1.002***	-0.134	-0.037	0.424	-1.323***									
	(0.067)	(0.186)	(0.343)	(0.107)	(0.393)	(0.461)									
Grade 4	0.067	1.013***	-0.028	0.019	0.481	-0.110	-0.008	-0.039	6.319				0.222	0.759***	1.107**
	(0.054)	(0.142)	(0.207)	(0.067)	(0.371)	(0.205)	(0.044)	(0.174)	(15.635)				(0.160)	(0.200)	(0.486)
Grade 5	0.037	1.029***	0.056	0.009	0.503	0.075	-0.085	-0.079	9.372	0.064	0.240	0.750	0.222*	0.923***	1.325**
	(0.042)	(0.123)	(0.139)	(0.052)	(0.365)	(0.222)	(0.064)	(0.197)	(23.422)	(0.098)	(0.320)	(1.164)	(0.114)	(0.174)	(0.543)
Grade 6	0.014	1.087***	0.177	-0.014	0.632*	0.177	-0.098	-0.009	9.524				0.205	0.207	17.805
	(0.056)	(0.129)	(0.154)	(0.066)	(0.353)	(0.238)	(0.077)	(0.185)	(23.418)				(0.275)	(0.389)	(14.846)
HH Asset Index	-0.002	0.000	0.001	-0.011	0.001	0.003	0.009	0.014	0.019	-0.022	-0.028	-0.064	0.013	-0.032	-0.042
	(0.007)	(0.008)	(0.017)	(0.010)	(0.012)	(0.021)	(0.012)	(0.014)	(0.030)	(0.024)	(0.038)	(0.063)	(0.028)	(0.031)	(0.039)
Held back	-0.105***	0.035	0.098	-0.099*	0.036	0.247**	-0.048	-0.017	3.178	-0.025	0.401	0.738	0.188	0.963***	1.357**
	(0.027)	(0.049)	(0.145)	(0.053)	(0.080)	(0.117)	(0.040)	(0.158)	(7.849)	(0.141)	(0.586)	(1.076)	(0.181)	(0.271)	(0.583)
Household size	0.004	0.001	-0.001	0.004	0.000	-0.002	-0.000	-0.000	-0.000	0.013	0.001	-0.070	0.006	0.015	0.031
	(0.003)	(0.002)	(0.007)	(0.004)	(0.003)	(0.012)	(0.003)	(0.001)	(0.006)	(0.009)	(0.005)	(0.057)	(0.009)	(0.015)	(0.068)
Father uneducated	-0.032*	-0.014	-0.053	-0.008	0.002	0.012	-0.018	-0.006	0.053	-0.141*	-0.093	-0.332	-0.065	-0.026	0.011
	(0.019)	(0.014)	(0.073)	(0.030)	(0.019)	(0.099)	(0.025)	(0.021)	(0.063)	(0.073)	(0.071)	(0.233)	(0.064)	(0.045)	(0.127)
Mother uneducated	0.043**	0.004	0.023	0.039	0.008	0.028	0.046*	0.007	0.050	0.133**	0.043	0.058	-0.038	0.034	-0.019
	(0.018)	(0.017)	(0.061)	(0.027)	(0.023)	(0.069)	(0.024)	(0.027)	(0.119)	(0.064)	(0.073)	(0.168)	(0.064)	(0.054)	(0.114)
Parental education missing	-0.015	-0.005	-0.028	0.002	0.012	-0.007	-0.004	0.011	0.102	0.050	-0.017	-0.441*	-0.106*	-0.002	0.041
	(0.019)	(0.015)	(0.090)	(0.030)	(0.028)	(0.126)	(0.027)	(0.015)	(0.113)	(0.063)	(0.057)	(0.234)	(0.060)	(0.055)	(0.135)
Teacher age	0.001	0.011**	0.011**	0.002	0.013	0.015**	0.002	0.014*	0.017*	-0.007*	-0.008	-0.023	0.002	0.008	-0.002
	(0.001)	(0.005)	(0.005)	(0.002)	(0.008)	(0.007)	(0.002)	(0.007)	(0.009)	(0.004)	(0.013)	(0.018)	(0.005)	(0.013)	(0.017)
Teacher female	-0.155***	-0.098	-0.036	-0.149***	-0.146	0.009	-0.211**	-0.104	-0.092	-0.238	-0.609*	0.117	-0.107	0.729	0.821
	(0.028)	(0.134)	(0.128)	(0.042)	(0.171)	(0.201)	(0.092)	(0.162)	(0.201)	(0.147)	(0.359)	(0.542)	(0.110)	(0.449)	(0.711)
Teacher from village	-0.077***	-0.008	0.000	-0.082***	0.019	-0.016	-0.041**	0.013	0.100	-0.102**	0.016	0.115	-0.022	0.027	0.030
	(0.013)	(0.045)	(0.062)	(0.020)	(0.096)	(0.098)	(0.020)	(0.045)	(0.112)	(0.044)	(0.092)	(0.131)	(0.049)	(0.148)	(0.199)

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Table 19 – *Continued from previous page*

	All children			High caste male			High caste female			Low caste male			Low caste female		
	coef/se	**coef/se**	**coef/se**	**coef/se**	**coef/se**	**coef/se**	**coef/se**	**coef/se**	**coef/se**	**coef/se**	**coef/se**	**coef/se**	**coef/se**	**coef/se**	**coef/se**
Teacher experience	-0.000	0.000	0.001	0.000	0.002	0.002	-0.001	-0.000	-0.035	0.003*	-0.002	0.176	0.001	0.001	0.167
	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.093)	(0.002)	(0.002)	(0.142)	(0.002)	(0.003)	(0.154)
Teacher education: FA	0.008	-0.008	-0.021	-0.021	-0.017	-0.024	0.012	0.024	0.040	0.067	-0.030	-0.181	0.105*	0.447	0.634*
	(0.018)	(0.060)	(0.072)	(0.027)	(0.094)	(0.105)	(0.024)	(0.097)	(0.127)	(0.067)	(0.139)	(0.142)	(0.060)	(0.274)	(0.333)
Teacher education: BA	0.034	0.022	0.074	0.024	-0.025	0.133	0.058	0.144	0.163	-0.097	-0.304	-0.242	0.264***	0.377	0.559*
	(0.023)	(0.115)	(0.113)	(0.036)	(0.172)	(0.215)	(0.038)	(0.173)	(0.176)	(0.066)	(0.308)	(0.259)	(0.093)	(0.280)	(0.323)
Teacher education: MA	0.078**	0.136	0.025	0.089	0.245	0.097	0.021	0.174	0.193	0.351**	0.110	-0.282	0.054	0.222	0.258
	(0.038)	(0.128)	(0.131)	(0.066)	(0.244)	(0.250)	(0.036)	(0.194)	(0.218)	(0.168)	(0.204)	(0.249)	(0.066)	(0.293)	(0.435)
Private school	0.149***	0.015	0.159	0.196***	0.001	0.172	0.082**	-0.034	0.058	0.058	-0.127	0.967	0.182**	0.090	-0.041
	(0.034)	(0.029)	(0.109)	(0.069)	(0.070)	(0.174)	(0.041)	(0.044)	(0.171)	(0.172)	(0.191)	(1.434)	(0.089)	(0.159)	(0.198)
School size	-0.000	-0.000	-0.001	-0.000	-0.000	0.000	0.000	-0.001	-0.002***	-0.000	0.002	0.001	-0.000*	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)	(0.003)
School facilities index	0.004	0.034	0.032	0.009	0.040	0.036	0.006	0.050	0.049	-0.004	-0.016	-0.024	-0.039***	0.027	0.004
	(0.006)	(0.023)	(0.020)	(0.008)	(0.030)	(0.025)	(0.011)	(0.036)	(0.042)	(0.020)	(0.092)	(0.073)	(0.015)	(0.025)	(0.035)
Constant	0.064	-0.044	-0.104	0.009	0.121	0.817	0.203	-0.463	-6.784	0.383	0.386	2.151	0.281	-1.112	-1.818
	(0.108)	(0.318)	(0.477)	(0.175)	(0.477)	(0.731)	(0.154)	(0.465)	(15.561)	(0.236)	(0.650)	(1.457)	(0.245)	(0.684)	(2.026)
Number of observations	1,364	1,364	1,364	556	556	556	466	466	466	209	209	209	133	133	133
R2	0.099	0.676	0.763	0.107	0.684	0.794	0.111	0.715	0.739	0.229	0.807	0.853	0.383	0.917	0.953
Fixed effect	None	School	Child	None	School	Child	None	School	Child	None	School	Child	None	School	Child

Notes: $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Outcome is switching between a high and low caste teacher. All specifications include time dummies, and standard errors clustered at the level of the fixed effect.

Table 20: Child attrition

	Low caste		**High caste**	
Round	Number	Percent	Number	Percent
1	60	9.35	186	9.3
2	230	35.83	684	34.2
3	348	54.21	1,098	54.9
4	4	0.62	32	1.6
Total	**642**	**100**	**2,000**	**100**

Table 21: Robustness Checks

Outcome: average of math, English and Urdu test scores		
	(1)	(2)
	Schools that pass the Monte Carlo CI test	Village-years that pass the Monte Carlo χ^2 test
Child high caste, teacher high caste	0.135	-0.090
	(0.148)	(0.102)
Child low caste, teacher high caste	0.273*	0.222***
	(0.152)	(0.084)
Observations	1550	2362
R^2	0.430	0.417

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All regressions include child, teacher and school controls, and time dummies.

Standard errors clustered at the level of the fixed effect (child).

Table 22: Teacher-Student Dyadic Caste Match

	(1) All Children	(2) High Caste	(3) Low Caste
Teacher and child belong to same caste group	-0.053	-0.033	-0.216**
	(0.053)	(0.058)	(0.102)
Observations	2642	2000	642
R^2	0.422	0.415	0.488

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All regressions include child, teacher and school controls, and time dummies.

Standard errors clustered at the level of the fixed effect (child).